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Who is participating in residential energy efficiency programs?

Exploring demographic and other household characteristics of participants in utility customer-funded energy efficiency programs

Margaret Pigman, Jeff Deason, Sean Murphy

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Acronyms and Abbreviations

ACS	American Community Survey
CBG	Census block group
DI	Direct install
HVAC	Heating, ventilation, and air conditioning
IQ	Income qualified
LEAD	Low-Income Energy Affordability Data
RECS	Residential Energy Consumption Survey

Executive Summary

Utility customer-funded energy efficiency programs benefit all customers by reducing the total electric system cost and also provide direct benefits to the participants. We study the relationships between participation rates in residential programs and demographic and other household characteristics. Understanding the current state of these relationships will help us assess the extent of current inequities in program participation and figure out what characteristics we need to target to achieve equitable outcomes.

We review previous work on this topic and compare it to our own primary analysis of four datasets. Using as consistent a methodology as possible, we study the impact of 11 demographic and household characteristics – income, education, race and ethnicity, limited English, energy poverty, tenure, householder age, homeownership, building vintage, building type, and urbanization. Our datasets have different scopes, strengths, and levels of detail, including one with household-level data at a national scale, two from New England at the zip code level, and one from a Midwestern state at the census block group level.

We employ both single-variable and multivariable models to study the relationships between these factors and program participation. The single-variable models describe the relationship between each factor and program participation, while the multivariable models seek to disentangle the effects of individual factors from other factors they are correlated with (e.g., income and education). Parsing these factors suggests specific opportunities for programmatic intervention.

Table ES-1 shows a high-level summary of results from our analysis and previous work. Overall, the table suggests there is room to improve equity of program participation. The clearest associations with energy efficiency program participation were with education and building type – higher education households and households in single-family homes were more likely to participate, and these relationships remained strong in multivariable analyses. The single-family results are in part structural – many programs are only available to single-family households – though our results suggest that these structural factors should be examined. The very clear impact of education on participation across program types suggests that program administrators may wish to explore strategies to better engage households and locations with lower educational attainment.

Results for race and income were somewhat less consistent, both in our analysis and in the existing literature. They depended on the statistical model, the individual program, and the particular racial and ethnic group being considered. Still, patterns emerged that suggest inequities regarding these factors that program administrators may wish to address. In single-variable models, income and participation were positively correlated except in income-qualified programs, although it was not always significant in multivariable models. The patterns were similar for Black heads of household but varied for other racial and ethnic groups.

One of our datasets allows us to compare two different participation rates for the same income-qualified program – the *overall* participation rate, or the share of *total* households in the geographic area who participated, and the *eligible* participation rate, or the share of *eligible* households in the geographic area who participated. We find that the results of the analysis depend on which rate is chosen. For example, higher income areas had a lower overall participation rate but a higher eligible participation rate for the income-qualified program – indicating that within the eligible low-income population, households in higher-income areas participated more.

Additional work could improve our understanding of equity in program participation and how to improve it. Possibilities include extending the analysis to more places with a wider variety of programs and demographics, closely considering the implications of using particular participation and equity metrics (including place-based vs. household-level metrics), and identifying design and delivery characteristics of particular programs that are successful at attaining equitable outcomes for replication elsewhere.

Table ES-1. Simplified summary of results

	Household income		Householder education		Black householder		Latino White householder		Other race / ethnicity		Limited English		Energy poverty		Householder age		Ownership		Tenure		Number of units		Vintage		Urbanization	
Residential Energy Consumption Survey (RECS)																										
Any assistance	—	—	▲	▲	—	—	▼	—	▼ —	▼ —			—	—	▲	—			▼	—	▼	▼	▼	▼	—	—
Lights	▼	▼	—	—	▲	—	—	—	—	▼ —			▲ —	—	—	—			—	—	▼	—	▼	▼	—	—
Audit	▼	—	▲	▲	—	—	—	—	—	▼ —			—	▼	—	—			—	—	▼	▼	—	—	—	—
Appliance rebate	▲	—	—	—	—	—	▼	▼	—	—			—	—	—	—			—	—	—	▼	—	—	▼ —	—
Appliance recycling	▲	—	—	—	▼	—	▼	—	—	—			▼ —	—	▲	—			▼	▼	▼	—	▼	▼	—	▲ ▼
Mass Save																										
Electric	▲	—	▲	▲	▼	—	—	▼	▼	▼ —	▼	—	▲	▲	▲	—	—	—	▲	—	▼	▼	▲ ▼	—	▼	▲
National Grid Rhode Island																										
Market rate	▲		▲		*		*		*		▼		▼		—		▲		—		▼		—		—	
Income qualified — eligible	▲		—		*		*		*		▼		▼		—		▲		—		▼		—		▼	
Income qualified — overall	▼		▼		*		*		*		—		▲		—		▼		—		—		—		▼	
Utility A (Midwest)																										
Any program	▲	▲	▲	▲	—	▲	—	▲	▲ ▼	—	▼	—	▼	▼	▲	▲	—	—	▲	▲	▼	▼	▼	—	▲	▲
Any market-rate program	▲	▲	▲	▲	▼	▼	—	▲	▲ ▼	—	▼	—	▼	▼	▲	▲	▲	▲	▲	▲	▼	▼	▼	▲	▲	▲
Income qualified audit & direct install	▼	▼	▲	▲	▲	▲	▼	—	▲ ▼	▲	—	▼	▲	—	—	▲	—	—	▲	—	▼	▼	▲	▼	▲	▲
Audit & direct install	▲	—	▲	▲	▲	▲	—	—	▼ —	—	—	—	▼	▼	▲	▲	—	—	▲	—	▼	▼	—	—	▲	▲
HVAC rebate	▲	▲	▲	▲	▼	▼	—	—	▲ ▼	—	▼	—	▼	▼	▲	▲	—	—	▲	▲	▼	▼	▼	▲	▲	▲
Appliance recycling	▲	—	▲	▲	▼	▼	▲	▲	▲ ▼	▲	—	—	▼	▼	▲	—	—	—	▲	—	▼	—	▼	—	▲	▲
Literature																										
	▲ 7 — 3	▲ 2	▲ 3	▲ 1	— 2 ▼ 1	▲ 1	▲ 1 — 2 ▼ 1	▲ 1	▲ 2 — 2 ▼ 2	▲ 1	▲ 1	▲ 1		▲ 1	— 1 ▼ 2	— 1	▲ 4	▲ 2		▼ 2	▼ 1	▲ 1 ▼ 2	▲ 1 ▼ 1	— 1	▲ 1	▲ 1

Key:

▲ participation increased as the variable increased, or was higher for households with the characteristic

▼ participation decreased as the variable increased, or was lower for households with the characteristic

— participation did not change based on the variable

blank : variable was not studied

gray columns contain single-variable results

unshaded (white) columns contain multivariable results

Multiple symbols indicate that the relationship varied depending on the subgroup or exact metric considered.

Numbers in the "Literature" rows indicate the count of studies that found a particular result.

* Racial and ethnic groups were not compared individually to the share of non-Latino White householders because of sample size. The share of non-Latino White heads of household in the zip code was positively correlated with the market-rate and *eligible* income-qualified participation rates but negatively correlated with the *overall* income-qualified participation rate.

1. Introduction

Utility customer-funded energy efficiency programs are a major delivery mechanism for residential energy efficiency investment in the United States, and therefore a key component of climate investment. These energy efficiency programs benefit all utility customers by reducing the total cost of electricity and gas delivery services. Households that participate receive additional direct benefits, which can include lower energy bills, improved home comfort, and better indoor air quality (IEA, 2019; Pigg et al., 2021). This motivates identifying which types of utility customers are currently accessing these programs, and which types are not, in pursuit of equitable outcomes.

In this report, we examine how participation rates in residential utility customer-funded energy efficiency programs vary by demographic and other household characteristics. First we review and summarize some previous research addressing this question. The methodologies and demographic factors vary widely across studies, and most studies only consider one factor (e.g., income or building type) at a time. Second we analyze four distinct datasets with a relatively consistent methodology, using multivariable models when we can to parse the effects of different factors.[1] We document how program participation in our data differs by these demographic and physical factors and compare our results to findings from previous studies.

Section 2 identifies a number of factors that might influence energy efficiency program participation and reviews prior research on these factors. Section 3 describes our data and methodology for the primary research we conduct in this report. Section 4 presents our results for each studied dataset. Section 5 brings our results together across our datasets and joins them with the prior literature. Section 6 offers conclusions for program administrators to consider, and Section 7 identifies additional research efforts that could further improve our understanding of the determinants of program participation and move towards more equitable program implementation.

2. Previous Work on Characteristics Influencing Participation in Energy Efficiency Programs

This section describes the demographic and physical characteristics that we study and the relationships previous studies have found between these characteristics and program participation. There are many pathways through which these characteristics might influence participation. For example, higher-income households may be more likely to have the capital required for investment (or be better able to access a loan with favorable terms). Products or services may be easier to access in a particular area. In some cases there are plausible reasons that a characteristic could either decrease or increase participation. For example, low-income households may participate less because they may be unable to afford to

[1] Single variable or univariate models reveal the relationship between a single factor and the outcome of interest, for example income and participation. However, there are many other factors related to income, such as education and race, which might affect participation. Multivariable or multivariate models reveal the relationship between a factor and the outcome when the other factors are held constant. This is sometimes referred to as "controlling" for the other variables.

replace broken or inefficient equipment, conduct deep retrofits, cover upfront costs in advance of receiving a program rebate, or pay a premium for efficiency. Conversely, these households may participate more because bill reductions and improvements in comfort and air quality may have a larger impact. Also, they may be eligible for federal and utility-sponsored income-qualified weatherization and efficiency programs. However, because these programs have higher costs for program administrators than market-rate programs, they are not funded in proportion to the share of low-income households in the area (Frick et al., 2021; Reames et al., 2019).

Table 1 summarizes findings from the studies described in the remainder of this section, categorized by data source.

Table 1. Summary of select previous work

Source	Place	Years covered	HH† income	HoH education	Black HoH†	Latino White HoH	Other race / ethnicity	Limited English	Energy poverty	HoH age	Ownership	Tenure	Number of units	Vintage	Urbanization
Survey data (household-level demographics)															
Burke & Cooper, 2013	National	2009-2011													
market rate			▲							▼	▲				
weatherization			—							▼	▲				
Cohn, 2015	National	2015			—	▲	▲								
DNV-GL, 2017	NY	2016-2017	▲	▲						▼	▲				
Frank & Nowak, 2016	CA	2010-2012	▲	▲	▼ —	▼ —	▼ —	▲						▲ ▼	
Illume et al., 2020	IN	2019	▲												
Navigant et al., 2020 *	MA	2013-2017	▲	▲				▲	▲		▲	▼	▼ ▲	—	
Research Into Action, 2019	OR	2018	—	▲	—	—	—			—	▲		▼		
Wemple et al., 2016 *	National	2013-2015													
market rate					▲	▲	▲								
weatherization					▲	▲	▲								
Utility data (place-based demographics)															
DNV-GL, 2019	MA	2013-2017	▲								▲				
Navigant, 2017 *	RI	2009-2015													
market rate			▲							—	▲	▼	▼		▲
income qualified			—							—	—	▼	▼		▲
Rubado et al., 2018	OR	2013-2017													
capital investment			▲				▲ ▼								▲
free to participant			—				▲ ▼								▲

Key:

▲ participation increased as the variable increased, or was higher for households with the characteristic

▼ participation decreased as the variable increased, or was lower for households with the characteristic

— participation did not change based on the variable

blank: variable was not studied

* included multivariable analysis

† HH is household; HoH is head of household

Multiple symbols indicate that the relationship varied depending on the subgroup or program considered.

Except where the results are split into two lines in the table, studies did not distinguish between market-rate and income-qualified programs.

2.1 Household Characteristics

2.1.1 Income

Multiple studies have examined the relationship between income and program participation. Some studies are based on self-reported program participation from surveys; others are based on program participation data from program administrators. In most cases they found that participation rates in energy efficiency programs tend to increase as household income goes up. Burke and Cooper (2013) conducted single variable analysis based on a national survey of 32,000 households on behaviors and attitudes related to energy use. They showed that higher-income households were more likely to report participating in utility-sponsored programs than low-income ones, with the exception of weatherization programs (which are most often available only to low-income households). A Navigant (2017) study of participation rates in market-rate and income-qualified whole-building efficiency programs found that their income metric was in the top five most influential factors (out of fourteen factors tested) for market-rate electric accounts but not for gas or income-qualified accounts. Among market-rate electric accounts, participation increased with income, as measured by the percent of area median income (AMI). Frank and Nowak (2016) found that low- and middle-income households were underrepresented among program participants relative to their share of total households, based on analysis of 16 program evaluations in California for the 2010-2012 program period. DNV-GL (2017) surveyed customers about Rochester Gas & Electric’s online marketplace for discounted energy efficient products and found that higher income households were more likely to have made purchases there. In a single variable analysis based on surveys and interviews in Massachusetts, Navigant et al. (2020) found that non-participants were more likely to be low and moderate income. However, when they added other variables to the analysis, income was no longer a consistent predictor of participation.

Rubado et al. (2018) found that participation tended to be higher in census tracts with higher incomes for 5 years of program participation data from Energy Trust of Oregon, except for programs that are provided at no cost to the participant. Similarly, DNV-GL (2019) found higher electric and gas savings in census block groups with lower shares of low-income households.

In other studies, income was not a significant factor influencing participation. Research Into Action (2019) found no significant difference in the income of participants and non-participants in Energy Trust of Oregon programs based on a telephone survey. Illume Advising et al. (2020) surveyed customers of Northern Indiana Public Service Company (NIPSCO) who did not participate in their home audit programs. The surveyed non-participants had a slightly higher proportion of households with incomes over $75,000 than in the service territory at large; the result was not tested for statistical significance.

Overall, although there were some instances where income was not associated with participation, in most cases higher-income households participated more. None of the studies found that participation increased as incomes declined.

2.1.2 Education

Four studies that compared the educational attainment of participants of energy efficiency programs found that post-secondary education is associated with higher participation. These studies cover 14 evaluations of California efficiency programs (Frank and Nowak, 2016), customers of Energy Trust of Oregon (Research Into Action, 2019), people who bought from Rochester Gas & Electric's online marketplace (DNV-GL, 2017), and Massachusetts residents (Navigant et al., 2020). Only Navigant et al. conducted a multivariable analysis, and their finding that non-participants were more likely than participants to only have a high school education held up in both their single- and multivariable analyses. The research findings were consistent – participation increased with educational attainment in all cases.

2.1.3 Race and Ethnicity

Previous studies of the impact of race and ethnicity on program participation have shown mixed results. In some cases, they have shown higher participation among non-White groups. In a multivariable regression analysis by Wemple et al. (2016) of a national survey of 32,000 households on behaviors and attitudes related to energy use, non-White groups were 1.38-2.52 times more likely to report participating in a variety of general and income-qualified efficiency programs than Whites. For most programs, the Asian and Pacific Islander group had the highest propensity to participate. The analysis controlled for 10 variables including homeownership, income, and household type. A marketing poll of 1,345 homeowners in five regions of the US (Cohn, 2015) indicated that Latinos were the most likely group to be interested in energy efficiency and to have made energy efficiency improvements in their houses within the last year. Also, Latinos and Asians were more likely to have participated in a utility-sponsored rebate program than Blacks or Whites (25-26% vs. 17-19%).

In other cases, the patterns varied between non-White groups. An analysis of 5 years of program participation data from Energy Trust of Oregon found that census tracts with a high proportion of Asians were the most likely to participate, while tracts with a high proportion of Native Americans were the least likely (Rubado et al., 2018). Tracts with higher racial and ethnic diversity tended to have more variation in participation rates than affluent White ones, perhaps because of differences in behavior among different racial and ethnic groups. Overall, though, those high diversity tracts had higher participation rates in programs with a cost to the participant. However, another study for Energy Trust of Oregon, this time based on survey results, found that there was no statistically significant difference in reported program participation based on race (Research Into Action, 2019).

Frank and Nowak (2016) found that Whites were overrepresented in California's whole-home retrofit and online/mail energy audit programs compared to their share of both the overall population and single-family homeowners. However, the proportion of participants in various racial and ethnic groups for the appliance and refrigerator recycling programs were consistent with the California population.

Overall, race and ethnicity were inconsistently associated with program participation. Non-White groups, particularly Latinos and Asians, often participated more than non-Latino Whites, although there were some cases where the relationship was reversed. In other cases, race and ethnicity had no impact on participation. Native Americans were only considered separately in one instance, but in that study they were the racial and ethnic group least likely to have participated (Rubado et al., 2018).

2.1.4 Limited English

Although it is often related to race and ethnicity, limited English presents another set of barriers. For example, program materials may be available only in a few languages (Cadmus, 2013).

Two studies that investigated the effect of language found that households with limited English were underrepresented in participant populations (Frank and Nowak, 2016; Navigant et al., 2020). However, partnering with community organizations and offering information in languages other than English can successfully engage these households. When Southern California Edison offered seminars in Chinese, Korean, and Spanish, three quarters of attendees who were surveyed afterwards reported installing some kind of energy efficiency equipment, and another three quarters reported changing their behavior (Cadmus, 2013).

2.1.5 Energy Poverty

Customers who spend a large portion of their income on or have trouble paying their utility bills have a greater incentive to reduce their energy consumption, which might increase participation. However, they are less likely to have funds to spend on efficiency upgrades, so we expect to see their participation concentrated in income-qualified programs.

Massachusetts residents who agreed or completely agreed with the statement that they worry about having enough money to pay their energy bills were more likely to have participated in a Mass Save program (Navigant et al., 2020). This was the only study we found that directly tested the impact of energy poverty on program participation.

2.1.6 Householder Age

None of the studies that looked at the influence of the age of the head of household found that older householders were more likely to participate; either younger householders were more likely to participate or age did not have an effect. Single variable analysis by Burke and Cooper (2013), based on a national survey of 32,000 households on behaviors and attitudes related to energy use, showed that younger heads of household were more likely to report participating in utility-sponsored efficiency programs. Similarly, a survey in Rochester Electric & Gas territory found that younger customers were more likely to have bought an efficient product from the online marketplace (DNV-GL, 2017). However, householder age, size of household, and marital status were not in the top five of fourteen variables with the most influence on participation in National Grid Rhode Island's whole-building retrofit programs, whether market rate or income qualified (Navigant, 2017). An analysis of phone surveys found no statistically significant difference in people who did and did not participate in Energy Trust of Oregon's programs based on age, household size, or the presence of a child in the house (Research Into Action, 2019).

2.1.7 Homeownership

Evidence both from customer surveys and data directly from the program administrator paired with the census indicates that homeowners are more likely to participate in efficiency programs than renters. Homeowners are more likely than renters to buy efficient products from Rochester Gas & Electric's online marketplace (DNV-GL, 2017). The increase in participation in Energy Trust of Oregon's programs for homeowners is statistically significant (Research Into Action, 2019). Participants in efficiency programs in Massachusetts are more likely to be homeowners than renters, although adding educational attainment to the analysis shows that there is no difference for renters with a college degree (Navigant et al., 2020). In a national survey of 32,000 households, respondents who were homeowners reported higher participation rates than respondents who were renters (Burke and Cooper, 2013). DNV-GL (2019) looked at the relationship between savings and the share of owner-occupied households in a census block group and found an overall increasing trend in savings as homeownership share increased.

Homeownership was not one of the top variables explaining participation in National Grid Rhode Island whole-house retrofit programs, but for both the market-rate and income-qualified programs homeowners were more likely to participate (Navigant, 2017).

While the strength of the relationship varied across the reviewed studies, they all found that homeowners were more likely to participate.

2.1.8 Tenure

Two analyses of the impact of the length of time someone has lived in their current unit found that long-time residents were less likely to participate. A multivariable analysis of participation rates in National Grid Rhode Island's whole-house retrofit programs showed that tenure was one of the top five most influential variables of the 14 variables they considered (Navigant, 2017). In the market-rate program, homeowners who had lived 3-15 years in their home were most likely to have participated. In the income-qualified program, participation by electric-account holders declined after 8 years of residence. A single variable analysis comparing the characteristics of participants and non-participants found that survey respondents who had moved in within the last 5 years were most likely to report that they had participated in one of Massachusetts's programs (Navigant et al., 2020).

2.1.9 Trust

Interviews and discussions in multiple studies raised the idea that trust in the utility or program administrator can impact participation. This can range from mistrust of government agencies and other entities that are part of the "system", to caution around opportunities that seem too good to be true and might be scams, to wariness of organizations who are seen as having broken promises (Navigant et al., 2020; Active Efficiency Collaborative, 2020; Cadmus, 2013). But trust can be built up through successive positive interactions. Once someone has participated in one efficiency program, they are more likely to participate in another one (Burke and Cooper, 2013; Wemple et al., 2016; Illume Advising et al., 2020).

2.2 Physical Characteristics of the Dwelling

2.2.1 Building Type

Overall, studies found that participation rates were higher in single-family homes. Although homes with up to 4 units were eligible for the single-family programs in Rhode Island, Navigant (2017) found that participants in the electric and gas market-rate programs were more likely to live in single-family homes than nonparticipants were. In fact, the number of units in the building was one of the top two variables linked to participation. Similarly, participants in efficiency programs in Oregon were statistically significantly more likely to live in single-family homes than non-participants were (RIA, 2019). A study in Massachusetts found that households living in small multifamily buildings (3-9 units) were underrepresented as program participants compared to single-family homes or large multifamily buildings (10+ units) (Navigant et al., 2020). Some of these findings may be related to the different ownership rates of the building types, as single-family homes are more often owned than other building types.

2.2.2 Vintage

Previous studies do not point to a clear relationship between building vintage and program participation. Age of the building was in the top five most influential variables for predicting participation in National Grid Rhode Island's whole-building retrofit programs (Navigant, 2017). For both the market-rate and income-qualified programs, participants were more likely to live in buildings built between 1930 and 2000 than nonparticipants. This finding was particularly pronounced for the gas accounts in the income-qualified program. On the other hand, in Massachusetts Navigant et al. (2020) did not find any substantial differences in participation based on vintage. In their overview of program assessments in California, Frank and Nowak (2016) found that there was a higher proportion of houses built before 1970 among participants in the whole home retrofit program than in the building stock overall. On the other hand, houses built after 2000 were overrepresented among people who participated in an online energy audit. These findings may suggest that vintage effects depend on program type.

2.2.3 Urbanization

Studies in both Oregon and Rhode Island found that participation rates were lower in rural areas than urban ones. In Oregon, the urban/rural divide was particularly strong for programs that required a capital investment (Rubado et al., 2018) but the result may have been confounded by differences in program offerings across service territories. In Rhode Island, the result held up in the multivariable analysis and was conducted in a single utility's service territory (Navigant, 2017).

2.3 Program Characteristics

Different efficiency programs require differing participation commitments. For example, rebate programs for heating, ventilation, and air conditioning (HVAC) equipment can leave a high up-front cost to the consumer and require hiring a contractor for installation. This may make these programs more easily available to higher income households. On the other hand, direct installation of efficient lights is accessible across income levels.

In their survey of 33 program evaluations in California, Frank and Nowak (2020) saw differences in participant characteristics based on the cost or time buy-in required for the program. Programs with higher buy-in tended to have participants who had higher incomes, had a college degree, had good English skills, and were White. While Rubado et al. (2018) found that households with higher incomes participated more in Oregon efficiency programs, the trend was more pronounced for programs that required a financial investment from the participant than those that did not.

3. Research Approach, Data and Methods

This section describes several datasets we leverage in our own analysis of the determinants of participation and methods we employ.

3.1 Data Sources

For our analysis in this report, we leverage efficiency program participation data from four sources:

- The 2015 Residential Energy Consumption Survey (RECS)
- Mass Save programs from 2013–2018
- National Grid Rhode Island programs from 2015–2017
- Programs offered by a Midwestern utility, here called Utility A, from 2017–2019

Table 2 provides a summary of these data sources. The remainder of this section describes each dataset in more detail.

The RECS data include demographic and household information, but our other datasets do not. In those cases we use demographic and household information from the American Community Survey (ACS) and Low-Income Energy Affordability Data (LEAD), as described in Section 3.1.4.

Table 2. Summary of participation data sources

Dataset	Geographic extent and specificity	Years covered	Demographics source	Participation variable	Program breakdown	Sample size
RECS	National – 10 census divisions	Data collected 2015–2016	Household survey	Whether household received assistance, yes/no	4 types of assistance	3,928 owner-occupied units
Mass Save	Part of Massachusetts – zip code	2013–2018	ACS, LEAD	Participant incentives ($) by zip code	None	472 zip codes over 6 years
Rhode Island	Rhode Island – zip code	2015–2017	ACS, LEAD	Eligible and overall participation rates by zip code[2]	2 programs	76 zip codes
Utility A	Portion of a Midwestern state – census block group (CBG)	2017–2019	ACS, LEAD	Count of participating addresses by CBG	4 programs	1,750 CBGs

3.1.1 Residential Energy Consumption Survey (RECS)

The RECS is a periodic effort by the Department of Energy to understand residential energy consumption by surveying a nationally representative sample of households.[3] Questions cover characteristics of the physical space as well as demographic and behavioral information about the occupants. We use the public microdata from the 2015 RECS in this analysis, which is presented at the census division level (Figure 1).[4] For the full text of all the questions used in the analysis, see Appendix A.1.

The 3,928 participating homeowners were asked about four types of energy efficiency assistance that we are able to study[5]:

Has your household received any of the following energy-related benefits or assistance for this home?

- Free or subsidized energy-efficient light bulbs
- Free or subsidized home energy audit
- Utility or energy supplier rebate for new appliance or equipment
- Recycling of an old appliance or equipment (e.g., a refrigerator)

[2] See Section 3.1.2.2 for the distinction between eligible and overall participation rates.
[3] https://www.eia.gov/consumption/residential/
[4] There are nine census divisions, but the RECS splits the Mountain division in two and reports the data in ten geographic bins.
[5] They were also asked about other types of energy-related assistance, but the number of households that reported receiving them was very small, so they were not included in the public microdata.

The biggest strengths of the RECS data for our analysis are that they are nationally representative and reported at the household level. This means that we know the demographic and housing characteristics of the respondents themselves; none of our other datasets define characteristics at the household level.

At the same time, there are several limitations to the RECS data. First, the question about energy assistance does not explicitly address utility customer-funded programs, so it is possible that the reported assistance did not come from such programs. That said, utility customer-funded programs are the dominant delivery mechanism for these types of assistance in the United States, so we suspect most reported assistance did come from such programs. Second, the data are reported at a high level of geographic aggregation. We do not have any specifics about the energy assistance available to the responding households; some of the households in the dataset may not have been able to access some types of assistance, for example due to lack of program availability or eligibility restrictions. Finally, the RECS survey only asked homeowners about receiving energy efficiency assistance, so we do not have insight into the behavior of renters.

3.1.2 Data at the Zip Code Level

We use three data sets from specific utilities or groups of utilities. Because none of these datasets provide demographic or physical characteristics at the household level, we use place-based Census data for our household and demographic characteristics. See Section 3.1.4 for more information on our use of Census data.

3.1.2.1 Mass Save

Mass Save is a consortium of six investor-owned utilities in Massachusetts that coordinates energy efficiency programs and reporting. They publish electricity and gas consumption, savings, and participant incentive data at the town and zip code level starting in 2013.[6] These data are from its member utilities and cover most of the efficiency programs in the state and 465 of Massachusetts' zip codes. We use data from 2013-2018. Programs run by municipal utilities are not included.

Based on regulatory reporting, income-qualified programs account for about a quarter of utility residential electric and gas program spending in Massachusetts. The other program types that account for large portions of the budget are whole-building audits and retrofits for both electricity and gas, lighting programs for electricity, and water and space heating programs for gas.[7]

These data come with three limitations related to their level of aggregation. First, they are not broken down by program; all residential reporting, including for income-qualified programs, is combined.[8] Second, the data are not broken down by utility service territory even though the programs are run by individual utilities and vary slightly among them. Third, the data are reported at the zip code level, so we

[6] https://www.masssavedata.com/Public/GeographicSavings?view=U
[7] E Source DSM Insights, Program Benchmarking, https://dsmi.esource.com/program-benchmarking/
[8] In Massachusetts, the Low-Income Energy Affordability Network (LEAN) offers no-cost programs to low-income households. The funding comes from multiple sources, including the utilities, state government, and the federal Weatherization Assistance Program (WAP). The Mass Save data only include the utility-funded savings and incentives.

do not know the characteristics of the households that received the participant incentives. We use place-based Census data for our household and demographic characteristics.

Another limitation of these data is that participation is not reported directly. Instead we use participant incentives[9] as a proxy.

As we investigated the Mass Save data, we realized that the variation in natural gas service availability across the participating utilities' territories was a significant driver of our results and confounded the relationships we were attempting to study. For that reason, we only present results for the Mass Save electricity programs.

3.1.2.2 National Grid Rhode Island

National Grid Rhode Island offers market-rate and income-qualified programs that both include free energy audits and direct installation of simple measures such as lighting, low flow showerheads, and smart power strips. The market-rate program provides targeted recommendations for further efficiency measures along with information about rebates and loan opportunities. The income-qualified program will weatherize the house and replace inefficient appliances and heating systems at no cost to the customer (Navigant, 2017).

Navigant studied the factors that are associated with participation in these programs for 2015 through 2017 in their report "Energy Efficiency Program Customer Participation Study" (Navigant, 2017). They used account- and household-level participation data, building characteristics, and demographic information. Due to data availability, the analysis covered the single-family programs (which apply to buildings with up to four units). Many of the insights from that analysis are included in Section 2 above.

While Navigant analyzed many of the factors that we are interested in, they did not look at education or race. However, Appendix A of their report contains cumulative participant counts and participation rates for each of Rhode Island's 76 zip codes broken out by program and fuel. We use those participation data in conjunction with data from the Census to analyze the associations with race and education.

We look at two different participation rates. The first rate is the "eligible participation rate" or the share of eligible customers that participated in the program. In this case, each customer in a building with up to four units is classified as being eligible for either the income-qualified or the market-rate program. Navigant did this classification and included the eligible participation rates in their report.[10] The second rate is the "overall participation rate" or the share of total households that participated. In this case, the total number of households is taken from the Census and does not vary based on whether or not they are eligible for the particular program whose participation rate is being calculated. This is the method

[9] Participant incentives are defined as a "budget category that includes funds paid by the reporting Program Administrator to or on behalf of customers or trade allies as rebates or in other forms." https://www.masssavedata.com/Public/Glossary

[10] Customers were classified as eligible for the income-qualified program if they were on one of the low-income rates or had participated in the income-qualified program (more recently than the market-rate program). Other factors were not considered when determining eligibility.

we use for our other datasets because we do not have information about the number of eligible customers. As discussed in Section 4.3, these two participation rates show differences in the way they relate to some studied factors – such as income – that are important to account for when interpreting results in other datasets.

The main strength of this dataset is that we can compare results based on the eligible and overall participation rates. The main limitation is that there are only 76 zip codes in Rhode Island, so the sample size is relatively small. In addition, we do not have household-level demographic data and use place-based data instead.

3.1.3 Data at the Census Block Group Level: Utility A

Utility A serves gas and electricity customers in the Midwest. Utility A's electricity and gas service territories are not identical. The data consist of counts of unique participating customers by program for 2017–2019 at the census block group (CBG) level. We analyze following residential efficiency programs:

- An appliance recycling program that picks up working refrigerators and freezers and gives participants a rebate.
- A HVAC rebate program that offers mail-in rebates for high efficiency heating and cooling equipment including furnaces, air conditioners, boilers, and smart thermostats.
- Two programs, one market rate and one income qualified, offering a free energy audit with recommended savings measures. Based on the fuels served by the utility, the customer may have any or all of the following installed during the audit: LEDs, water efficiency measures, and water heater pipe insulation. Duct sealing may also be improved, and low-income customers may receive a programmable thermostat.

In addition to program-level analysis, we look at aggregated program participation in any program or any market-rate program. The Any Program and Any Market-Rate Program categories include participation in three other residential programs without enough participants to analyze on their own.

A significant strength of this dataset is that participation is broken down by program. The data are also relatively disaggregated, being at the level of a census block group instead of a zip code. The main limitation is that there is no household-level demographic data, so we must use place-based data instead.

3.1.4 American Community Survey (ACS) and Low-Income Energy Affordability Data (LEAD)

Except for the RECS, we do not have household-level building characteristics or demographic information. In order to conduct analysis of these factors, we use data from the American Community Survey (ACS), which is conducted each year by the Census Bureau. We collect ACS data on both building characteristics (type, vintage, urban or rural location) and household characteristics (annual income, educational attainment, race and ethnicity, limited English, age of the head of household, tenure in the living space, and homeownership). See Appendix A.2 for a summary of the specific variables used.

We use data from the ACS at two geographic levels: census tracts and census block groups (CBGs). A census tract is a portion of a county with between 1,200 and 8,000 people, with a target size of 4,000 people. A block group is a portion of a tract with 600 to 3,000 people.[11] Utility A provided data at the block group level, so we use the ACS data without aggregation. However, the Mass Save and Rhode Island participation data are at the zip code level, so we aggregate ACS tract-level data to the zip code level. See Appendix A.2 for information about how we do the aggregation.

We also draw data from the Department of Energy's Low-Income Energy Affordability Data (LEAD) Tool.[12] This tool calculates mean energy burden, or the share of income that is spent on energy, at the tract level based on ACS data. All Utility A block groups in a given tract therefore receive the same LEAD mean energy burden in our data; we aggregate and calculate zip code means for MA and RI zip codes. The RECS contains household-level data related to energy burden, which we use (rather than LEAD data) when analyzing that dataset.

3.2 Methodology

We use descriptive statistics and regression models to illustrate and interrogate the dependence of the participation metrics on eleven demographic and physical factors:

- Income – household income
- Education – highest level of education achieved
- Race and ethnicity – self-identified race and ethnicity into the Census categories[13]
- Limited English[14]
- Tenure – number of years in the current dwelling
- Age – age of head of household
- Homeownership – occupied by the owner or renters
- Vintage – year the dwelling was built
- Building type – number of dwelling units in the building
- Urbanization – being in an urban or rural area
- Energy poverty[15]

We estimate relationships between these factors and our participation metrics using both single-variable and multivariable regression models. Conceptually, these models tell us somewhat different things. The single variable models we view as descriptive: they tell us whether there is a relationship

[11] https://www.census.gov/programs-surveys/geography/about/glossary.html
[12] https://www.energy.gov/eere/slsc/maps/lead-tool
[13] Unless otherwise noted, we combine the race and ethnicity variables into four categories: White alone, not Hispanic or Latino ("non-Latino White"); White alone, Hispanic or Latino ("Latino White"); Black alone ("Black"); Other ("Other").
[14] The Census defines a limited-English-speaking household as one in which no one over the age of 14 speaks only English or speaks English "very well." https://www.census.gov/topics/population/language-use/about/faqs.html
[15] The metric of energy poverty depends on the dataset. For the RECS, we use questions such as "In the last year, how many months did your household reduce or forego expenses for basic household necessities, such as medicine or food, in order to pay an energy bill?" See Appendix A.1 for more information. For Mass Save and Utility A, we use energy burden, or the percent of income spent on energy.

between each factor and program participation that is robust enough to likely not be due to chance. The multivariable models are somewhat more diagnostic: they explore whether the descriptive results may be explained in part by other factors. Some of the factors are correlated (e.g., income and education), so including them both in multivariable models helps distinguish which one is more influential. The single-variable results may in some ways be more important to an equity analysis: if certain households are participating more than others, these outcomes may be inequitable regardless of whether they are driven in part by some other factor. Still, we feel both analyses are important, and our multivariable models (which are not common in the literature) suggest targets for programmatic intervention.

Because we have household-level data for the RECS, making our participation outcome binary (yes or no), we use a logistic model. For our other datasets, where our participation outcomes are rates (such as the share of households in a census block group that participated), we use linear probability models. See Appendix A.3 for more details.

4. Results

This section provides a visual and narrative description of our analysis results, stepping through each dataset one at a time. See Appendix B for correlation matrices of the explanatory variables and Appendix C for the full regression tables. Section 5 is organized by household characteristic and relates our results to the existing literature reviewed in Section 2.

4.1 RECS

Table 3 summarizes the rates at which all RECS homeowners reported that they received the four types of energy-related assistance we study. 23% of the 56,670 homeowners who responded to the survey reported receiving at least one of the studied types of assistance.

Table 3. RECS energy-related assistance rates. "Any of the above" is not the sum of the "Participants" column because some households received multiple kinds of assistance. The values in the "Total responses" columns vary by type of assistance because not all homeowners answered every question.

	Participants	Non-participants	Total responses	Participation rate
Free or subsidized energy-efficient light bulbs	4,635	51,975	56,610	8%
Free recycling of old appliance or equipment	5,235	51,255	56,490	9%
Utility or energy supplier rebate for new appliance or equipment	3,600	52,950	56,550	6%
Free or subsidized home energy audit	1,800	54,420	56,220	3%
Any of the above	*13,125*	*43,545*	*56,670*	*23%*

In our regression analysis, household location had a significant association with receipt of energy assistance for all four types we study, individually as well as overall. Households in the South census region (all divisions) and the West North Central census region received statistically significantly lower levels of overall energy efficiency assistance than those in the Northeast census region, which had the highest rate (Figure 1, Figure 2). The differences were substantial: when controlling for other relevant factors, households in these areas were 10-20 percentage points less likely to have received at least one kind of assistance. Other regions and divisions are not statistically significantly different from the Northeast overall. These relative participation rates were broadly similar to the levels of utility customer-funded spending on energy efficiency in the regions during the period of RECS data collection (Gilleo et al., 2015).

These findings were similar for the individual types of assistance, although the differences were typically larger. For example, households in the West South Central division were 12 percentage points less likely on average to have received free or subsidized efficient light bulbs than those in New England. The notable exception is appliance recycling, which appears to be relatively rare in New England. Households in the Middle Atlantic division, the Midwest region, and the Mountain South and Pacific divisions all show statistically significantly *higher* rates of receipt of appliance recycling assistance than households in New England.

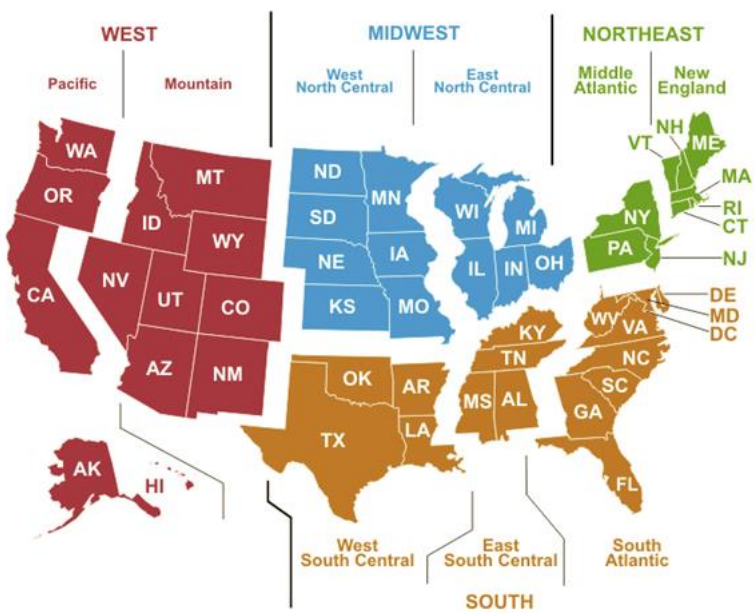

Figure 1: Census regions and divisions. The RECS further breaks down the Mountain census division into Mountain South (Arizona, New Mexico, and Nevada) and Mountain North (Colorado, Idaho, Montana, Utah, and Wyoming). Source: https://www.eia.gov/consumption/commercial/maps.php#census.

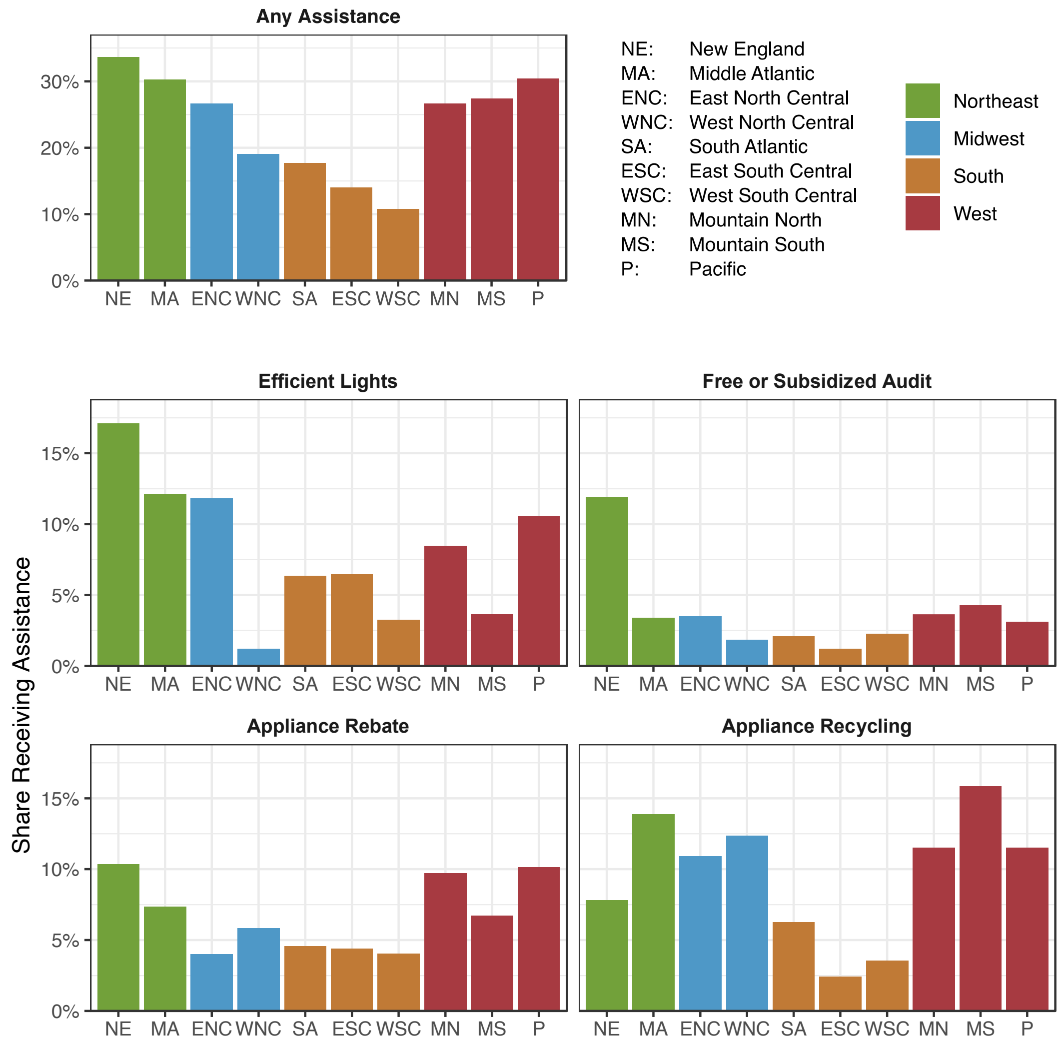

Figure 2: RECS share receiving assistance by Census division

Table 4 shows a high-level summary of the relationships between the demographic and household characteristics we study with the receipt of energy efficiency assistance.

Table 4. RECS summary of results

	Household income		Householder education		Black householder		White, Latino householder		Other race / ethnicity householder		Energy poverty		Bill or repair assistance		Householder age		Tenure		Number of units		Vintage		Urbanization	
Any assistance	—	—	▲	▲	—	—	▼	—	▼ —	▼ —	—	—	▲	▲	▲	—	▼	—	▼	▼	▼	▼	—	—
Lights	▼	▼	—	—	▲	—	—	—	—	▼ —	▲ —	—	▲	▲	—	—	—	—	▼	—	▼	▼	—	—
Audit	▼	—	▲	▲	—	—	—	—	—	▼ —	—	▼	▲	▲	—	—	—	—	▼	▼	—	—	—	—
Appliance rebate	▲	—	—	—	—	—	▼	▼	—	—	—	—	▲	▲	—	—	—	—	—	▼	—	—	▼ —	—
Appliance recycling	▲	—	—	—	▼	—	▼	—	—	—	▼ —	—	▲	▲	▲	—	▼	▼	▼	—	▼	▼	—	▲ ▼

Key:

▲ receipt of assistance was higher for households with the characteristic or a higher value of the factor

▼ receipt of assistance was lower for households with the characteristic or a lower value of the factor

— participation did not change based on the characteristic

Multiple symbols indicate that the relationship varied depending on the subgroup.

▆ gray columns contain single-variable results

☐ unshaded (white) columns contain multivariable results

In addition to Census division, another factor that was significantly associated with receipt of all four types of *energy efficiency* assistance we study was receipt of assistance with *bill payments or appliance repairs* (Figure 3). Our multivariable regression analysis indicates that households that received assistance paying for energy bills or repairing appliances were 20 percentage points more likely on average to receive at least one type of energy efficiency assistance than otherwise equivalent households that did not. This finding presumably reflects efforts by program administrators to target programs to these households.

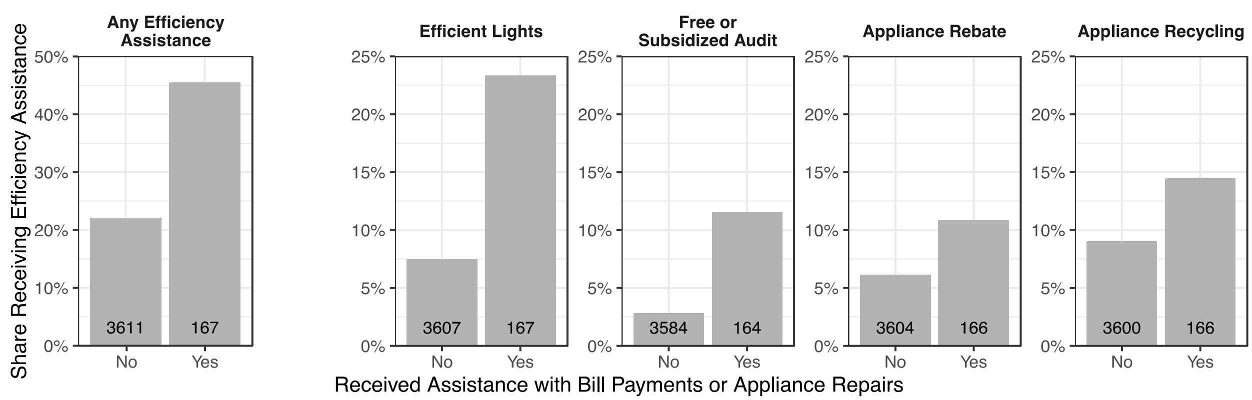

Figure 3: RECS share of households receiving efficiency assistance by receipt of assistance with bill payments or appliance repairs. Numbers indicate count of respondents.

Household income did not show any statistically significant relationship with overall receipt of energy efficiency assistance, either on its own or when controlling for other variables (Figure 4). When we look at the different forms of assistance separately, however, we see that some efficient lighting assistance and audit assistance was likely targeted at lower-income households. Compared to households with a self-reported annual income less than $20k, households making at least $80k were about 5 percentage points less likely on average to receive assistance with efficient lighting when controlling for other factors. For appliance rebate and recycling assistance, higher-income households were more likely to receive assistance. These differences are statistically significant in single-variable models, but not in multivariable models, indicating that factors correlated with income – such as education, homeownership, etc. – may help explain the results. We discuss this issue further in Section 5 below.

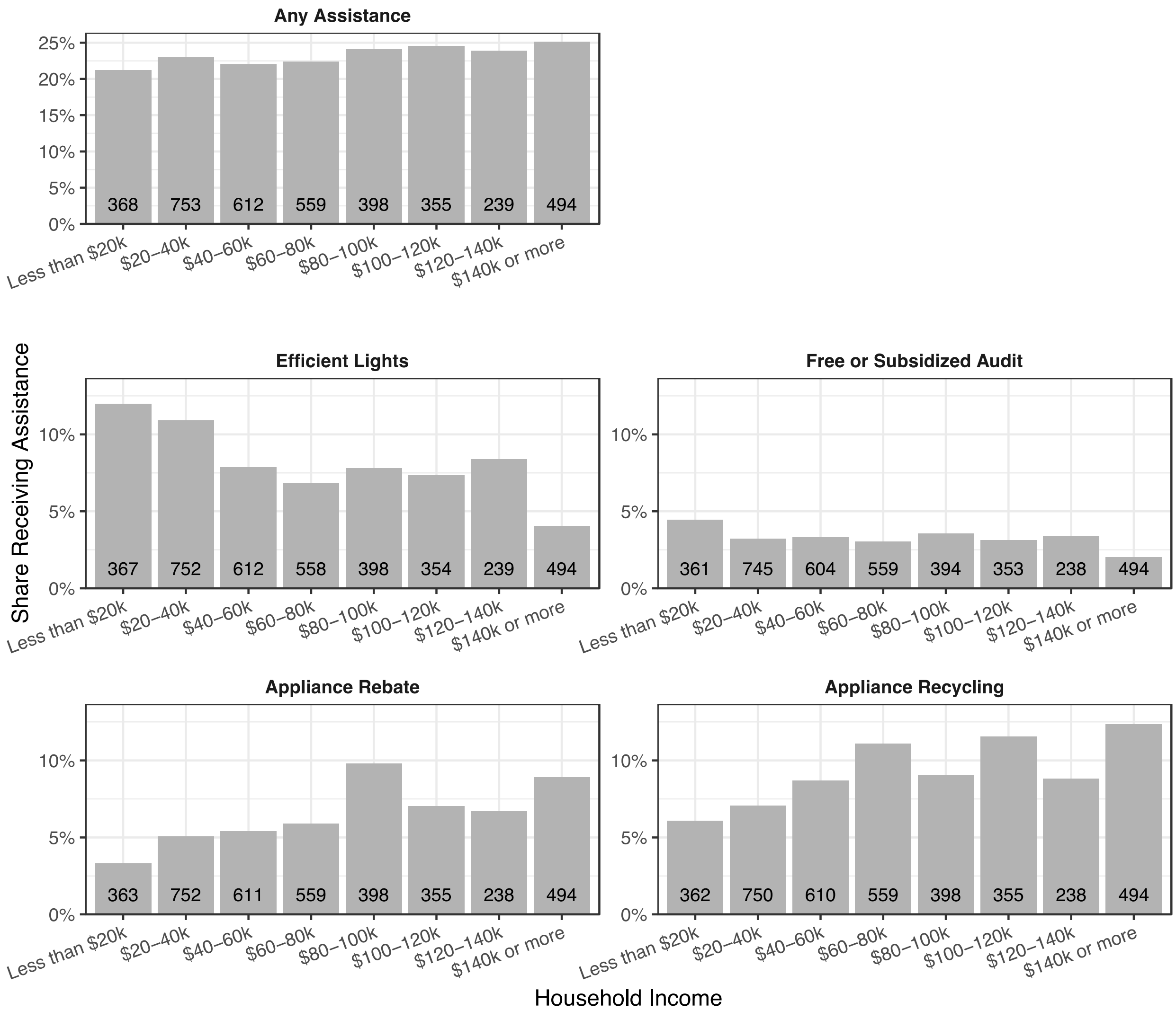

Figure 4: RECS share of households receiving assistance by annual household income. Numbers indicate count of respondents in the income bin.

Households whose heads of household had more years of education were more likely to receive energy efficiency assistance, both overall and for each individual program type other than efficient lighting. When controlling for other factors, heads of household with at least a Bachelor's degree were 8 percentage points more likely to receive some type of assistance than those without a high school degree. Households with Internet access also received energy efficiency assistance at higher rates than those without, all else equal. Both of these variables may relate to a household's means to find and evaluate information about the availability and benefits of energy efficiency assistance.

The relationship between energy assistance and race and ethnicity depended on the particular racial and ethnic group as well as the presence of control variables. When controlling for the other factors, Black heads of household and those who selected two or more races did not show statistically significantly different rates of energy efficiency assistance receipt than non-Latino White heads of household. However, most other racial and ethnic groups were less likely to receive some type of energy assistance than non-Latino White heads of household. American Indian or Alaska Native and Asian heads of household were less likely to receive assistance overall. American Indian or Alaska Native heads of household were less likely to receive efficient lights or audit assistance; Native Hawaiian or Other Pacific Islander heads of household were less likely to receive audit assistance; and Latino White heads of household were less likely to receive appliance rebates.

Beyond income, we investigate three variables related to energy poverty: frequency of keeping the home at an unhealthy temperature, reducing or forgoing basic necessities due to home energy bills, and receiving a disconnect notice. In most cases these variables are not statistically significant, especially in multivariable models.

Households in multifamily buildings of 5 or more units and households in mobile homes received statistically significantly lower levels of overall energy efficiency assistance than those in single-family detached buildings in most cases.[16] The reflexive explanation for this finding is the challenge of reaching renters with programs due to split incentives. However, that explanation does not apply here, since the survey responses we study are homeowner-only; our results indicate that *owners* of units in larger buildings and mobile homes accessed less energy efficiency assistance. The pattern only holds for free and subsidized audits and appliance rebates; there was no statistically significant difference in receipt of assistance for efficient lighting or appliance recycling based on building type.
Households in new buildings (those built after 2010) received less energy efficiency-related assistance than those in old buildings (those built before 1950), both overall and for lighting and appliance recycling programs specifically. It is no surprise that there would be more demand for energy efficiency assistance in old homes, which are more likely to lack efficient lighting and to need to upgrade appliances.

While census division was one of the most influential variables tied to receipt of efficiency assistance, the other locational characteristic we consider, urban vs rural, was generally not associated with receipt of assistance in a statistically significant fashion.

[16] Because only homeowners were asked about their participation in energy efficiency programs, more than 80% of the respondents lived in single-family detached homes. This means that the sample sizes in the other categories are relatively small and therefore that results are less likely to be statistically significant.

4.2 Mass Save

Table 5 shows a high-level summary of the relationships between the demographic and household characteristics we study with electric incentive payments.

Table 5. Mass Save summary of results

	Household income	Householder education	Black householder	Latino White householder	Other race / ethnicity householder	Limited English	Energy burden	Householder age	Ownership	Tenure	Number of units	Vintage	Urbanization
Electric incentives	▲ —	▲ ▲	▼ —	— ▼	▼ ▼ —	▼ —	▲ ▲	▲ —	— —	▲ —	▼ ▼	▲ —	▼ ▲

Key:

▲ per household incentives increased as the percentage of households in the zip code with the characteristic increased

▼ per household incentives decreased as the percentage of households in the zip code with the characteristic decreased

— participation did not change based on the variable

Multiple symbols indicate that the relationship varied depending on the subgroup.

gray cells contain single-variable results

unshaded (white) cells contain multivariable results

In a single-variable model, income was significantly correlated with zip code mean income, with higher-income zip codes receiving higher incentives per household (Figure 5). However, when controlling for the other demographic and physical characteristics we study, income had no statistically significant relationship with incentives.

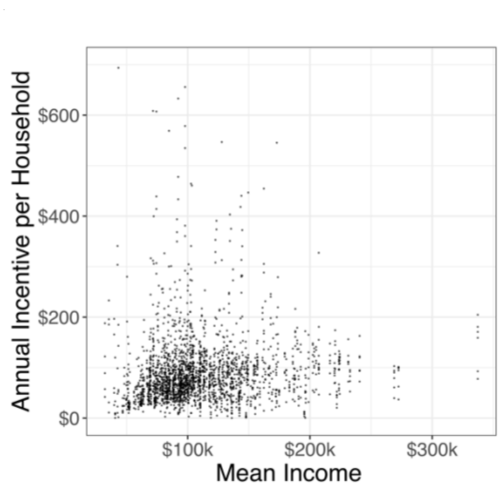

Figure 5: Mass Save annual incentives per household by zip code mean income

Education, on the other hand, was significantly correlated with incentives in both single- and multivariable models. In both cases, zip codes with a greater percentage of heads of household with a Bachelor's or graduate degree received higher incentives per household (Figure 6).

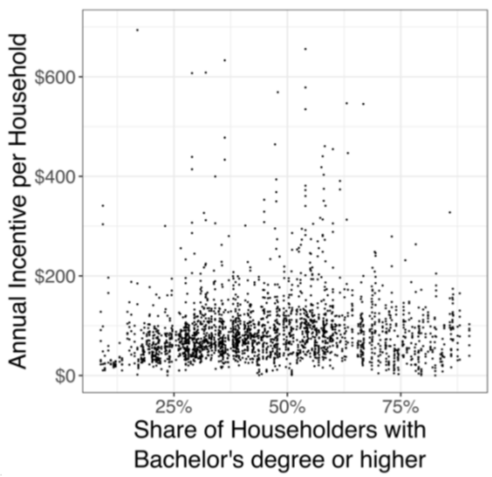

Figure 6: Mass Save average annual incentives per household by share of householders in the zip code with a Bachelor's degree or higher

A higher percentage of non-Latino White heads of household in a zip code was associated with higher incentives in both single- and multivariable models. While zip codes with a higher percentage of Black heads of household received lower incentives on average, the relationship was not significant in the multivariable model, indicating that other factors accounted for the difference. However, the percentage of Latino White heads of household in the zip code was only significant in the multivariable model, indicating that zip codes with a higher percentage of Latino White heads of household received lower incentives than average given the other characteristics of the zip codes.
In terms of energy burden, zip codes with a higher burden received higher electric incentives – an increase of 1 percentage point in energy burden was associated with a $20/household/year increase in electric incentives. Because zip codes with lower mean incomes did not receive higher incentives, this result may indicate that participation was particularly strong in zip codes that consumed more energy than otherwise similar zip codes.

We consider several factors related to the house itself: building type, vintage, and urbanization. The only factor with a consistent relationship with household incentives was building type; zip codes with higher percentages of single-family homes received higher incentives on average.

4.3 National Grid Rhode Island

Table 6 shows the eligible and overall participation rates for National Grid Rhode Island. Because only a fraction of the total households qualify for any particular program, the overall participation rates are lower than the eligible participation rates, particularly for income-qualified programs.

Table 6. National Grid Rhode Island eligible and overall participation rates

Program	Participants	Eligible accounts	Eligible participation rate	Overall participation rate
Market-rate electric	33,544	324,491	10.3%	8.1%
Market-rate gas	7,992	186,934	4.3%	1.9%
Income-qualified electric	9,202	27,908	33.0%	2.2%
Income-qualified gas	1,446	14,462	10.0%	0.4%

The sample size of 76 zip codes was too small for the multivariable analysis we conduct for the other datasets, so we only present single variable results for Rhode Island (Table 7). Because the analysis is single variable, we cannot disentangle the individual effects of the variables. In Rhode Island, education and race/ethnicity are both highly correlated with income (Table B - 2), and our analysis will not reveal how much a result is driven by one variable versus the other.

Table 7. National Grid Rhode Island summary of single-variable results

	Household income	Householder education	Non-Latino White householder	Limited English	Energy burden	Householder age	Ownership	Tenure	Number of units	Vintage	Urbanization
Market rate	▲	▲	▲	▼	▼	—	▲	—	▼	—	—
Income qualified — eligible	▲	—	▲	▼	▼	—	▲	—	▼	—	▼
Income qualified — overall	▼	▼	▼	—	▲	—	▼	—	—	—	▼

Key:

▲ participation increased as the percentage of households in the zip code with the characteristic increased

▼ participation decreased as the percentage of households in the zip code with the characteristic decreased

— participation did not change based on the variable

Figure 7 shows that the overall participation rate was positively correlated with mean income in the zip code for the market-rate program and negatively correlated for the income-qualified program. This is to be expected because not as many households qualify for the income-qualified program in zip codes with higher mean incomes. On the other hand, the *eligible* participation rate was positively correlated with the mean income for both the market-rate and income-qualified programs: a higher share of eligible households participated in the income-qualified program in zip codes with higher mean incomes. This difference may imply that the behavior of low-income households depended on the characteristics of their higher-income neighbors. Or it may imply that among eligible households, higher-income households were more likely to participate.

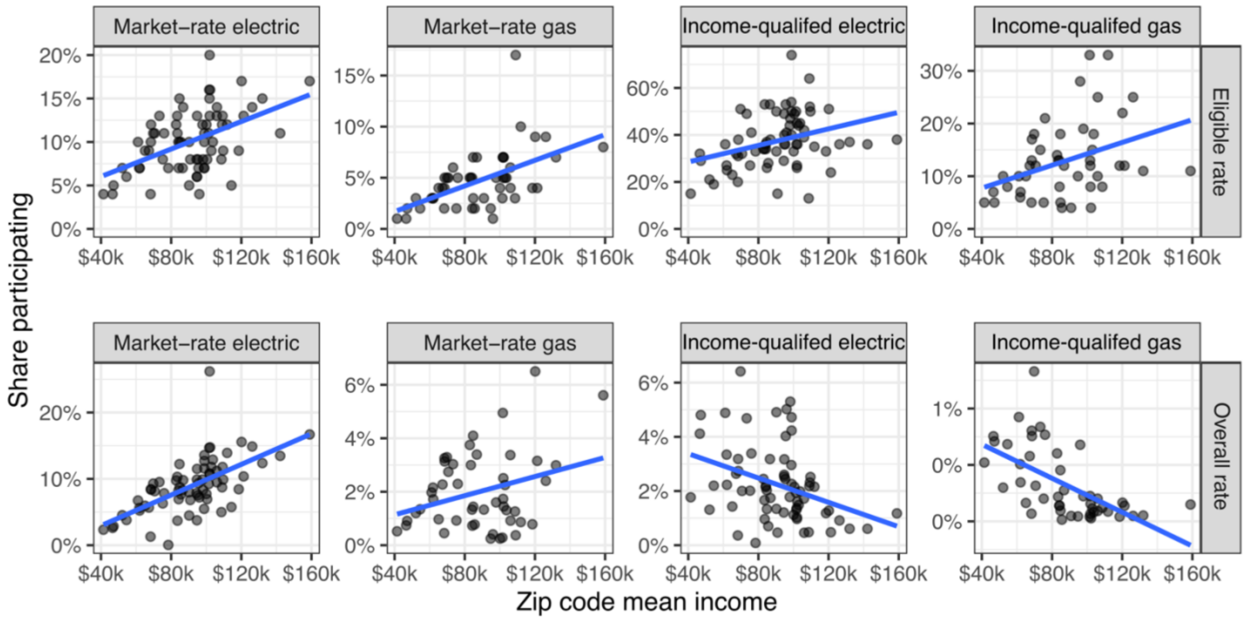

Figure 7: National Grid Rhode Island program participation by zip code mean household income

The relationship between eligible and overall participation rates and the share of heads of households in the zip code with a Bachelor's degree or higher was analogous to what we find for mean income (Figure 8). Education and income are strongly related in general (see Appendix B), so it is not surprising that the patterns closely track each other.

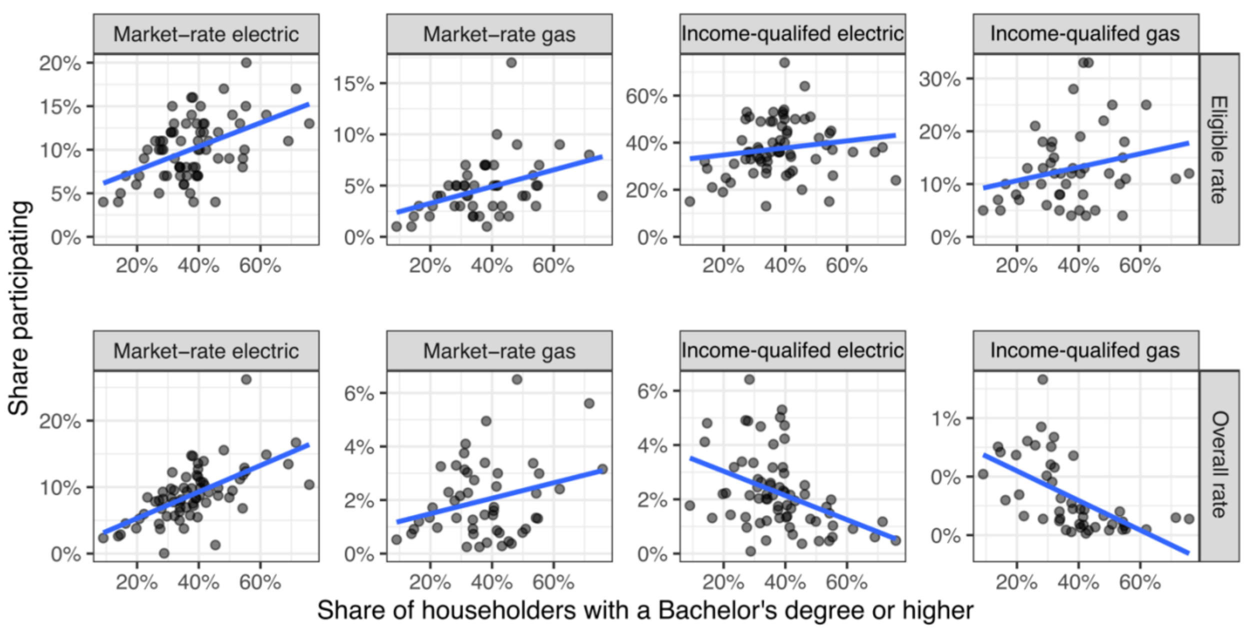

Figure 8: National Grid Rhode Island program participation by share of householders with a Bachelor's degree or higher

Figure 9 shows the relationship between program participation and the share of households in the zip code headed by a non-Latino White person. More than half of the zip codes have at least 90% non-Latino White householders, so none of the other racial or ethnic groups had a statistically significant relationship with participation rate on their own. However, taken as a binary variable, market-rate participation and eligible income-qualified participation were higher in zip codes with a greater share of non-Latino White heads of household. The direction of the relationship was reversed for the overall participation rate in the income-qualified program, in similar fashion to the reversals observed for income and education.

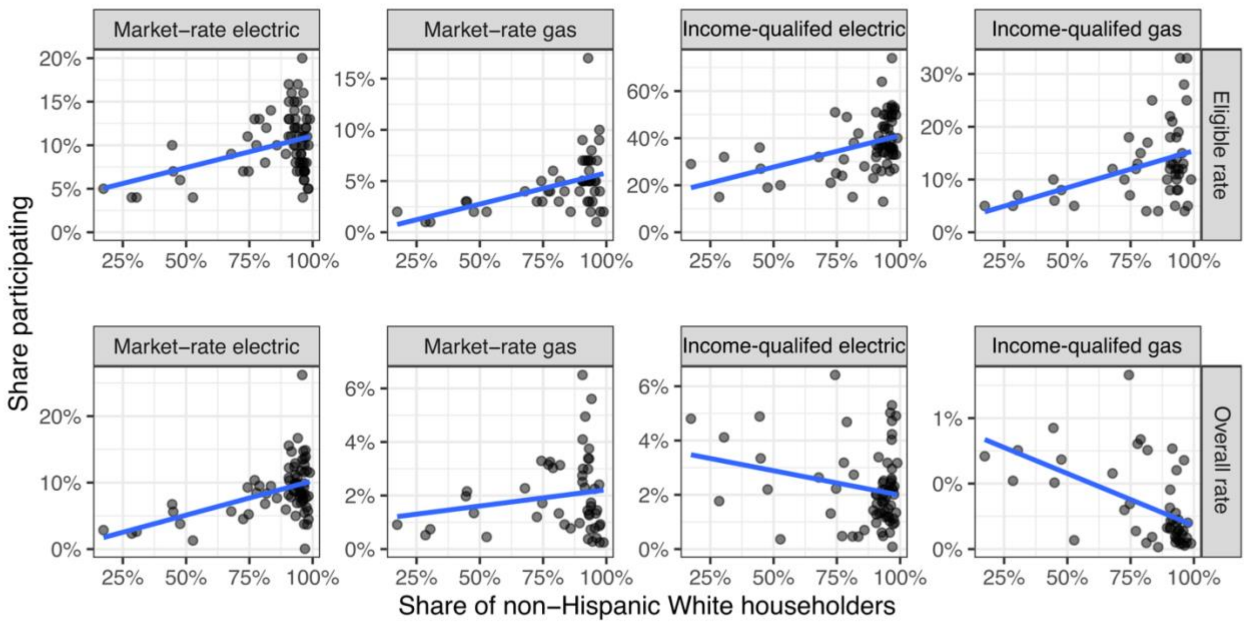

Figure 9: National Grid Rhode Island program participation by share of non-Latino White householders

As shown in Table 7 we also observe reversals in the relationships between participation and both energy burden and homeownership. Lower energy burden and higher homeownership rate were associated with lower overall participation rates but higher eligible participation rates.

4.4 Utility A

Table 8 shows the number of participants and participation rates for Utility A's four largest residential programs for 2017–2019. The HVAC rebate program was by far the largest, so results for this program are generally very similar to those for Any Market-Rate Program and for Any Program.

Table 8. Utility A program participation rates

Program	Participants	Rate
HVAC Rebate	22,251	2.51%
Appliance Recycling[17]	5,985	0.80%
Audit & direct install (DI)	2,309	0.26%
Income-qualified (IQ) audit & direct install (DI)[18]	2,500	0.28%
Any Market-Rate Program	*30,532*	*3.44%*
Any Program	*32,900*	*3.71%*

Table 9 shows a high-level summary of the results for Utility A. Relationships between block group demographics and program participation were broadly similar across the programs. Factors correlated with higher participation were a higher proportion of the population over 25 years old with some postsecondary education; a lower mean energy burden; and being in a metropolitan area. CBGs with a higher proportion of householders 55 years or older and living in buildings with less than 5 units also had higher participation rates on average.

Table 9. Utility A summary of results

	Household income		Householder education		Black householder		Latino White householder		Other race / ethnicity householder		Limited English		Energy burden		Householder age		Ownership		Tenure		Number of units		Vintage		Urbanization	
Any program	▲	▲	▲	▲	—	▲	—	▲	▲▼	—	▼	—	▼	▼	▲	▲	—	—	▲	▲	▼	▼	▼	—	▲	▲
Any market-rate program	▲	▲	▲	▲	▼	▼	—	▲	▲▼	—	▼	—	▼	▼	▲	▲	▲	▲	▲	▲	▼	▼	▼	▲	▲	▲
IQ audit & DI	▼	▼	▲	▲	▲	▲	▼	—	▲▼	▲	—	▼	▲	—	—	▲	—	—	▲	—	▼	▼	▲	▼	▲	▲
Audit & DI	▲	—	▲	▲	▲	▲	—	—	▼—	—	—	—	▼	▼	▲	▲	—	—	▲	—	▼	▼	—	—	▲	▲
HVAC rebate	▲	▲	▲	▲	▼	▼	—	—	▲▼	—	▼	—	▼	▼	▲	▲	—	—	▲	▲	▼	▼	▼	▲	▲	▲
Appliance recycling	▲	—	▲	▲	▼	▼	▲	▲	▲▼	▲	—	—	▼	▼	▲	—	—	—	▲	—	▼	—	▼	—	▲	▲

Key:

▲ participation increased as the percentage of households in the CBG with the characteristic increased

▼ participation decreased as the percentage of households in the CBG with the characteristic decreased

— participation did not change based on the variable

Multiple symbols indicate that the relationship varied depending on the subgroup.

■ gray cells contain single-variable results

□ unshaded (white) cells contain multivariable results

However, there were some factors whose associations varied across programs, most prominently race and income. CBGs with lower median household incomes had statistically significantly higher participation rates in the income-qualified (IQ) program. However, lower income was associated with a statistically significant *decrease* in Any Market-Rate Program and Any Program participation. Median

[17] Appliance Recycling was an all-electric program, so we use only households in Utility A's electric territory to calculate participation rate.

[18] Because we do not have eligible participant counts, we use overall participation rates. We calculate the IQ audit & DI participation rate based on the number of households in the CBG even though not all of the households are eligible.

income was significantly associated with participation in the market-rate audit & direct install or appliance recycling programs only in single-variable models. Most of these results are not surprising given the single variable relationships seen in Figure 10.[19]

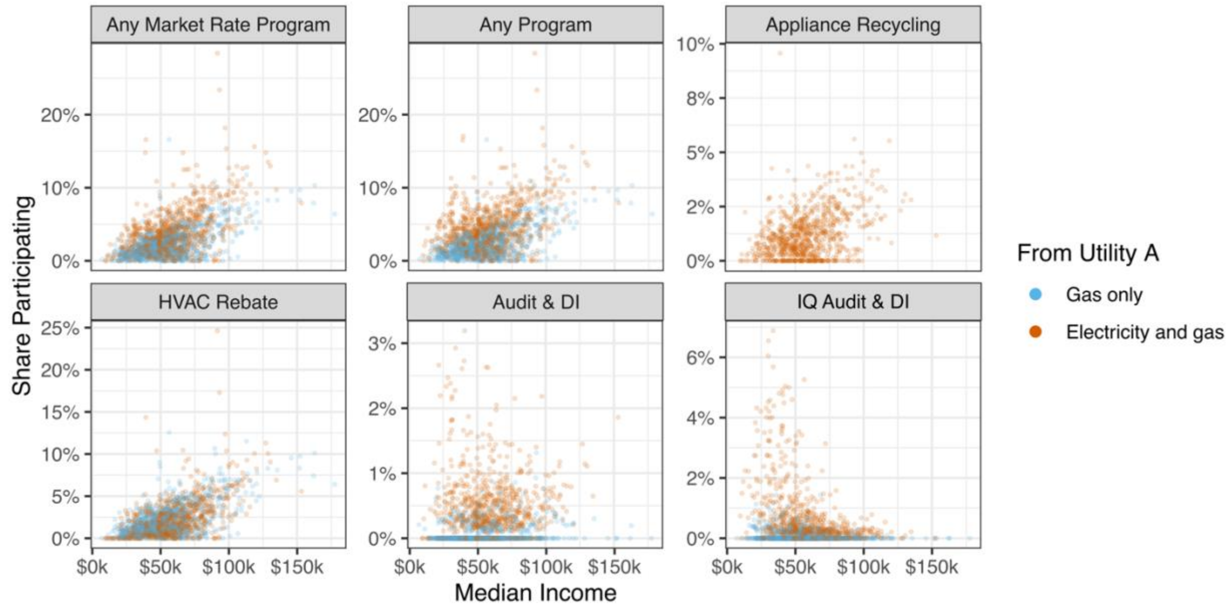

Figure 10: Utility A program participation by CBG median income

Figure 11 shows the relationship between program participation and the share of the households in the CBG with a non-Latino White head. Although it only considers that single variable, the general patterns that emerge visually are consistent with the statistical analysis that controls for our other demographic and household characteristics.

CBGs with a higher proportion of Black heads of household had higher participation in the audit & direct install programs (both the income-qualified and the market-rate programs). The relationship was reversed for appliance recycling, HVAC rebates, and Any Market-Rate Program. For every increase of one percentage point in the proportion of Black heads of household in the CBG, participation in the IQ direct install program rose by 2.4% and participation in the HVAC rebate program dropped by 1%; the changes were smaller for the other programs. In the Any Program results, the former effect dominated the latter: households with Black heads of household showed higher overall participation than those with non-Latino White heads of household, all else equal.

CBGs with a higher proportion of Latino White heads of households did not show statistically significantly different participation than non-Latino-White-headed households in the IQ program. However, they did have higher participation rates in both Any Market-Rate Program and Any Program categories. Again, all of these effects emerge from a model that controls for income and other factors, so they appear to be specifically related to race and ethnicity.

[19] In the case of the appliance recycling program, the multivariable statistical analysis shows that the positive visual association between median income and can be accounted for by other demographic and housing characteristics.

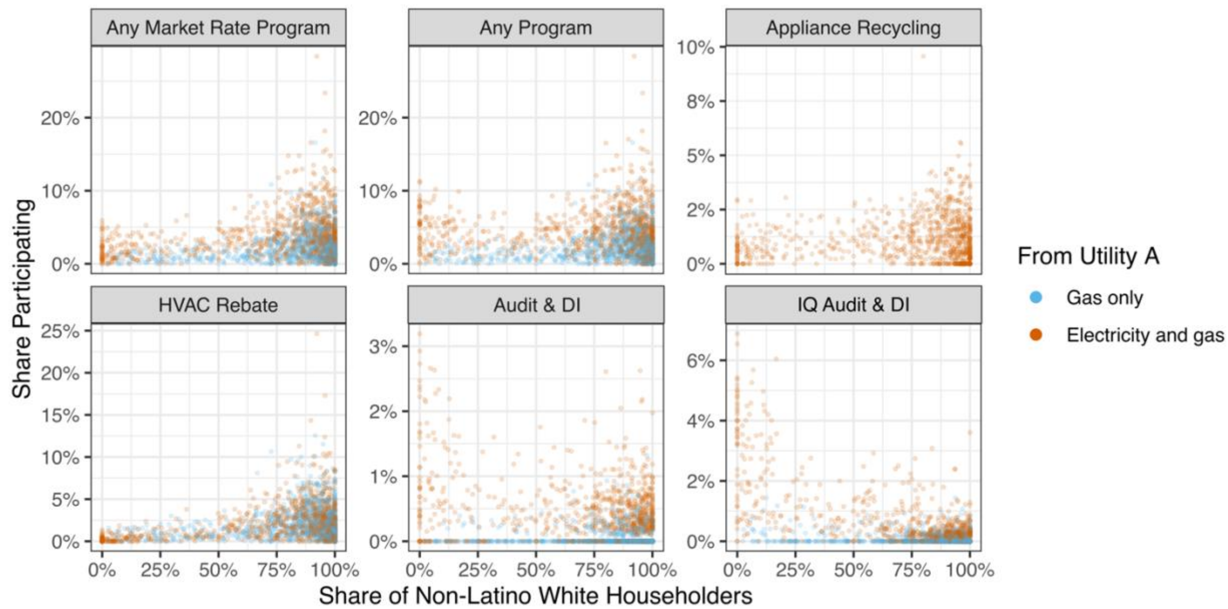

Figure 11: Utility A program participation by share of non-Latino White householders

The share of limited-English households had substantially different relationships with participation in the single- and multivariable models. When considered on its own, the share of limited-English households was negatively correlated with participation in the HVAC rebate program, Any Program, and Any Market-Rate Program. However, when controlling for other factors these relationships were no longer significant. Instead these CBGs with more limited-English households had lower participation in the IQ program in a statistically significant fashion.

Except for the IQ program, higher mean energy burden was negatively correlated with participation. Because this was true in single- as well as multivariable models, the effect of energy burden was in addition to the effect of income. For the IQ program, mean energy burden was positively associated with participation in the single variable but not multivariable model, indicating that mean energy burden itself did not have a direct effect on participation.

CBGs with higher shares of owner-occupied units had higher rates of Any Program participation, and this relationship was statistically significant.

5. Comparison of Findings Across Datasets and With Existing Literature

While there is a lot of variation in the relationships between the demographic and housing factors that we consider and the receipt of energy efficiency assistance, some general patterns do emerge from the analysis.[20] Table 10 shows a high-level summary.

[20] In Section 4 we are careful to use precise language to refer to the variables and the different ways they are defined in our datasets. In this section we are describing overall patterns and use words such as "participation" and "income" in more general ways that can apply to all of the analyses.

Table 10. Simplified summary of results

	Household income		Householder education		Black householder		Latino White householder		Other race / ethnicity		Limited English		Energy poverty		Householder age		Ownership		Tenure		Number of units		Vintage		Urbanization	
Residential Energy Consumption Survey (RECS)																										
Any assistance	—	—	▲	▲	—	—	▼	—	▼ —	▼ —			—	—	▲	—			▼	—	▼	▼	▼	▼	—	—
Lights	▼	▼	—	—	▲	—	—	—	—	▼ —			▲ —	—	—	—			—	—	▼	—	▼	▼	—	—
Audit	▼	—	▲	▲	—	—	—	—	—	▼ —			—	▼	—	—			—	—	▼	▼	—	—	—	—
Appliance rebate	▲	—	—	—	—	—	▼	▼	—	—			—	—	—	—			—	—	—	▼	—	—	▼ —	—
Appliance recycling	▲	—	—	—	▼	—	▼	—	—	—			▼ —	—	▲	—			▼	▼	▼	—	▼	▼	—	▲ ▼
Mass Save																										
Electric	▲	—	▲	▲	▼	—	—	▼	▼	▼ —	▼	—	▲	▲	▲	—	—	—	▲	—	▼	▼	▲ ▼	—	▼	▲
National Grid Rhode Island																										
Market rate	▲		▲		*		*		*		▼		▼		—		▲		—		▼		—		—	
Income qualified — eligible	▲		—		*		*		*		▼		▼		—		▲		—		▼		—		▼	
Income qualified — overall	▼		▼		*		*		*		—		▲		—		▼		—		—		—		▼	
Utility A (Midwest)																										
Any program	▲	▲	▲	▲	—	▲	—	▲	▲ ▼	—	▼	—	▼	▼	▲	▲	—	—	▲	▲	▼	▼	▼	—	▲	▲
Any market-rate program	▲	▲	▲	▲	▼	▼	—	▲	▲ ▼	—	▼	—	▼	▼	▲	▲	▲	▲	▲	▲	▼	▼	▼	▲	▲	▲
Income qualified audit & direct install	▼	▼	▲	▲	▲	▲	▼	—	▲ ▼	▲	—	▼	▲	—	—	▲	—	—	▲	—	▼	▼	▲	▼	▲	▲
Audit & direct install	▲	—	▲	▲	▲	▲	—	—	▼ —	—	—	—	▼	▼	▲	▲	—	—	▲	—	▼	▼	—	—	▲	▲
HVAC rebate	▲	▲	▲	▲	▼	▼	—	—	▲ ▼	—	▼	—	▼	▼	▲	▲	—	—	▲	▲	▼	▼	▼	▲	▲	▲
Appliance recycling	▲	—	▲	▲	▼	▼	▲	▲	▲ ▼	▲	—	—	▼	▼	▲	—	—	—	▲	—	▼	—	▼	—	▲	▲
Literature																										
	▲ 7 — 3	▲ 2	▲ 3	▲ 1	— 2 ▼ 1	▲ 1	▲ 1 — 2 ▼ 1	▲ 1	▲ 2 — 2 ▼ 2	▲ 1	▲ 1	▲ 1		▲ 1	— 1 ▼ 2	— 1	▲ 4	▲ 2		▼ 2	▼ 1	▲ 1 ▼ 2	▲ 1 ▼ 1	— 1	▲ 1	▲ 1

Key:

▲ participation increased as the variable increased, or was higher for households with the characteristic

▼ participation decreased as the variable increased, or was lower for households with the characteristic

— participation did not change based on the variable

blank : variable was not studied

gray columns contain single-variable results

unshaded (white) columns contain multivariable results

Multiple symbols indicate that the relationship varied depending on the subgroup or exact metric considered.

Numbers in the "Literature" rows indicate the count of studies that found a particular result.

* Racial and ethnic groups were not compared individually to the share of non-Latino White householders because of sample size. The share of non-Latino White heads of household in the zip code was positively correlated with the market-rate and *eligible* income-qualified participation rates but negatively correlated with the *overall* income-qualified participation rate.

When considering market-rate programs, in general participation was higher among higher-income households, more educated households, households without limited English, older heads of household, homeowners, and buildings with fewer units. Black heads of household tended to participate less in market-rate programs than non-Latino White heads of household. All these patterns also emerged in the reviewed literature, with the exception of age (which few reviewed studies addressed). It appears there is opportunity to improve equity of participation in these programs.

Income-qualified programs showed very different patterns. When looking at overall participation rates, lower-income households and Black heads of household participated more in these programs, although households in multi-unit buildings still participated less. However, the method of calculating participation rates can have a large impact on the results. For the National Grid Rhode Island data we are able to compare the share of total households in the zip code who participated (overall participation) with the share of eligible households in the zip code who participated (eligible participation). In the case of income-qualified programs, we see a different relationship between *overall* and *eligible* participation and the variables tested. Specifically, a higher share of eligible low-income households in higher-income, more highly educated, and more White areas participated in income-qualified programs. This implies that the same types of inequities that arise in market-rate programs may appear within the eligible populations of income-qualified programs or that the characteristics of the neighborhood affected the participation rate of low-income households.

Because of the importance of participation metric for income-qualified results, we are cautious about interpreting results for income-qualified programs from our other three datasets where we do not have eligibility information. A similar pattern might also be observed if eligibility based on living in a single- versus multi-family or owned versus rented home were taken into account.

Many of the factors we study are correlated with each other[21], and our multivariable models attempt to isolate their individual impacts. When we do so, education stands out as a consistent predictor of program participation. In almost every case, increased education was associated with increased receipt of efficiency assistance, and in no case was it associated with decreased receipt in a multivariable model. Indeed, in certain cases (e.g., income-qualified programs), the effect of education became clearer in a multivariable model. These findings are consistent with the four studies discussed in Section 2.1.2 that investigated education. Income and race/ethnicity, conversely, were less well correlated with participation, though the relationships outlined in the paragraphs above did remain statistically significant in some cases. Massachusetts, Rhode Island, and the Midwestern state all have a higher proportion of householders who are non-Latino Whites than the country as a whole, so evidence from more racially and ethnically diverse locations would be valuable.

While efficiency can be an important strategy for reducing energy burden, our results suggest that efficiency programs were not reaching households with the highest burdens in many cases. In the RECS data, our most direct proxies for energy burden were not statistically significant except for receiving a

[21] See Appendix B for correlation matrices.

free or subsidized energy audit, in which case the more burdened households received less assistance. However, assistance with bill payments and appliance repairs was strongly positively correlated with all of the forms of efficiency assistance. For Utility A, participation in the market-rate programs and Any Program was not only lower in CBGs with lower median incomes, but also negatively correlated with the Census tract's mean energy burden – meaning that households with higher energy burdens participated *less*, all else equal. The only instance in which participation and energy burden were positively correlated was for Mass Save electric incentives. This last finding is consistent with the survey-based study of Mass Save programs that found that people who worry about having enough money to pay their energy bills were more likely to have participated in an efficiency program (Navigant et al., 2020). We do not study energy burden directly in the National Grid Rhode Island data, but the fact that eligible participation rates declined based on the zip code's mean income implies that the households with the lowest incomes (and likely highest energy burdens) were not participating.

Along with education, the factor with the most consistent relationship with receipt of efficiency assistance was building type. It was statistically significant in most multivariate models, and households in single-family homes or apartment buildings with less than 5 units were more likely to receive assistance than households in larger buildings or those in mobile homes. This is consistent with previous studies.

The relationship between homeownership and program participation in our multivariable models was much weaker than when considering this factor on its own.

6. Conclusion

As Table 10 shows, certain types of utility customers participated more than others in energy efficiency programs. These findings may point program administrators toward program design or delivery changes in pursuit of more equitable participation outcomes.

Education stands out as a consistent predictor of participation, with more educated heads of household – or households in higher-educated areas – participating more. Education is reliably associated with greater participation in all types of studied programs when controlling for other factors – more so than other factors such as income and race/ethnicity. This finding suggests that programs may need to make specific efforts to target low-education households or locations to improve equity in program participation.

Income and race/ethnicity may be the first factors that spring to mind when considering equity in program participation. Our results, and those in the literature, are not as clear for these factors as for education, but do suggest reason to attend to them in program delivery.

Regarding income, in many cases higher-income households or those from higher-income areas participated more in market-rate programs. This finding often, though not always, held up when controlling for other factors such as education. In several cases our results suggested that households in lower-income areas participate more in income-qualified programs, which of course we would expect to be true. However, in the one dataset that allowed us to consider the share of *eligible* households that participate in these programs, eligible low-income households that lived in high-income areas participated more than those that lived in low-income areas. So, even among income-qualified programs there is reason for concern about reaching eligible customers equitably with respect to income.

Our results were more variable with respect to race and ethnicity. Individual programs showed different associations between participation and specific racial or ethnic groups. Even just looking at the two studied income-qualified programs (National Grid Rhode Island's and Utility A's), the association between race and participation depended on the participation metric used and the particular racial group. Different program outreach strategies may be particularly important to the participation rates of different racial and ethnic groups. The results from the literature regarding these factors are also varied.

One common goal of energy efficiency programs is reducing energy costs for households that struggle to pay those costs. However, our results and those in the literature do not necessarily show that programs in general are effectively targeting households with high energy burdens. Indeed, in several cases these households participated *less* than households with lower energy burdens. This finding suggests a clear opportunity for program administrators to modify their targeting, especially as program administrators can directly observe which customers are behind in their bill payments or have their service cut.

When considering potential modifications to program design or delivery in the interest of creating equitable outcomes, program administrators must first define what outcomes they are seeking, and consider what outcomes they can directly act on. As an example, our and others' results suggest that households in very newly built homes participated less, but this finding may not raise equity concerns: homes with new appliances and equipment, and in most cases built to more stringent building energy codes, often have less reason to participate in an energy efficiency program. We also find considerable regional variation in program participation: households in the South census region participated less and those in the Northeast participated more. This is likely due to differences in program availability and funding, rather than differences in participation rates among eligible households. Such regional differences are more difficult for individual program administrators to address, as they relate to differences in state-level decisions about the allocation of resources and regulation. However, program administrators can more directly act on many other differences in participation rates identified here.

Our findings highlight the importance of carefully choosing the metrics for studying equity in program participation and whether they will allow the desired question to be answered. As our Rhode Island data analysis emphasizes, outcomes can be quite different when considering eligible participation rates vs. overall participation rates, reversing the direction of the association in some of our results.

To assess equity in program participation, a researcher or program administrator must first decide which participant characteristics are relevant for equity and should be examined. Income, race and ethnicity, and energy burden are among those most commonly discussed. Our findings suggest that education be considered as well, because it was the characteristic most consistently associated with participation. Urbanization and building type, particularly single- versus multi-family homes, were also consistently associated with participation. Differences in participation based on these factors may or may not raise equity concerns, but it might be beneficial to intentionally decide whether or not to consider them.

Our findings also point to the importance of carefully considering program eligibility, in two ways. First, program eligibility influences the demographic characteristics of who can participate. Program administrators have been offering free and expanded programs for low-income households, for example, as a means of addressing concerns that those who need assistance might not receive it. Programs seeking equitable outcomes will very likely employ this and other eligibility tests going forward.

Second, as our results in Section 4.3 demonstrate, eligibility tests can complicate the analysis of who is participating, particularly when using place-based demographic data. For example, participation will be higher in low-income areas for programs with income eligibility requirements, but participation may still be higher among the highest-income households who are eligible. This dynamic can also obscure the association between participation and variables associated with the eligibility requirement, such as race and ethnicity, education, or housing type in the case of income. Many programs and interventions use place-based metrics for targeting their activities,[22] so program administrators will need to carefully define equity metrics, and carefully interpret outcomes.

While this report draws directly on data from four different datasets, and indirectly on the findings of a dozen other studies, readers should be cautious about generalizing the results. In some cases only a handful of studies speak to a particular factor, and in some cases results diverged across different program administrators and program settings. Additional research would have high value. Moreover, this report says little about *how* to change program design and delivery to achieve different participation outcomes. More effort to identify potential strategies and test their effectiveness is warranted, and should be a priority as program administrators, regulators, and policymakers devote increasing attention to this topic. Section 7 goes into more detail on future work that would provide additional value.

7. Future Work

This report provides the most comprehensive overview of the determinants of energy efficiency program participation that we are aware of. Nevertheless, the evidence base for answering this question is fragmented and results are at times contradictory. Considerable additional work could be devoted to this topic. Specific possibilities include:

[22] Two examples are the Community Reinvestment Act (https://www.federalreserve.gov/consumerscommunities/cra_about.htm), which evaluates banks based on the credit they extend to low- and moderate-income neighborhoods, and the Department of Housing and Urban Development's income limits (https://www.huduser.gov/portal/datasets/il.html), which determine place-based eligibility for various housing programs.

- Evidence from additional settings. Table 10 reflects results from thirteen studies (including ours). Only four of these studies (including ours) conducted any multivariable analysis. Hundreds of utilities and program administrators run energy efficiency programs across the country, with different types of programs serving different populations. Additional evidence, particularly multivariable analysis of programs in a variety of parts of the country, would be very helpful to supplement our conclusions here and to begin to parse some of the additional questions below. In addition, the locations that we study have a higher proportion of non-Latino Whites than the country overall, so it would be especially useful to study settings with more racial and ethnic diversity.
- Closer assessment of program eligibility when studying determinants of participation. Since we got distinctly different results from the National Grid Rhode Island data depending on whether program eligibility is taken into account, household-level data that include program eligibility would be very valuable for understanding the determinants of participation among eligible households. These data are particularly important for income-qualified programs since the demographics of the eligible households may not be the same as the CBG or zip code they live in.
- Design of place-based metrics to assess equity in participation (or other outcomes). The gold standard dataset for equity assessment would include household-level data with program eligibility information, but this is difficult to find and collect. This project would look for combinations of data and analysis methods using place-based data that yield the same associations between demographics and participation as the gold standard, and could be employed in other settings where household-level data are not available. Approaches could include multivariable analysis of place-based demographics and univariate analysis of place-based demographics with eligibility information.
- Effects of program design and delivery. In this report we illustrate the relationships between factors and program participation, but we generally could not identify the reasons for those relationships – though we have suggested explanations where they arise. However, some of the relationships are not universal. Examining Table 10 reveals several factors – such as race and energy burden – that have different relationships with participation in different settings. Presumably, additional studies could reveal other factors that merit similar scrutiny. By examining the targeting practices and delivery mechanisms of programs that achieve different results, we may come to better understand how to achieve desired program participation outcomes.
- Greater leveraging of EM&V reports. Utilities and program administrators often conduct surveys of their customers, which can include household-level demographic information, for their EM&V reports. We found and discussed findings from several such studies, but our search was not exhaustive. Although the demographic data collected and analysis methods vary widely, the geographic spread and number of programs covered may allow us to start grouping different directional results into categories. For example, race might tend to be associated with program participation differently for whole home and lighting programs.

- Implementation and analysis of pilot program approaches specifically targeted to achieve desired participation outcomes. As opposed to the previous bullets – which would leverage existing variation in program delivery to understand how that variation influences participation – this approach would explicitly test the impact of a change in program design or delivery to understand its impact on participation. Such approaches would allow clearer attribution of causality to particular approaches – especially where pilots employed randomized control trials or related approaches that facilitate causal inference. Analysis of novel approaches depends on program administrators implementing such approaches in a fashion that can be readily analyzed.
- Studying the distribution of benefits directly (as opposed to participation, as we do here). The Justice40 Initiative (and, likely, other similar initiatives at other levels of government) is considering appropriate ways to define and measure the benefits of energy efficiency and clean energy interventions. With these definitions and metrics in hand we can build on the approaches used here to study the demographic characteristics of the CBGs that are receiving more and less of those benefits. For example, energy savings and incentive dollars are available for some utilities and programs to facilitate the analysis.

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Appendix A. Methodological Details

A.1 RECS Survey Questions and Variables

The RECS questions used in the analysis are:

- Which best describes your home?
    - Mobile home
    - Single-family house detached from any other house
    - Single-family house attached to one or more other houses (for example: duplex, row house, or townhome)
    - Apartment in a building with 2 to 4 units
    - Apartment in a building with 5 or more units
- Is your home owned by you or someone in your household, rented, or occupied without payment of rent?
- When was your home built?
- When did your household move in?
- How often do you or other members of your household find your home too drafty?
- In your home, do you or any members of your household access the Internet?
- What is your age?
- Are you Hispanic or Latino?
- What is your race? Please select all that apply.
- What is the highest degree or level of school you have completed?
- Including all income sources, which category best describes the total combined income of all household members for the last year, before taxes and deductions?
- In the last year, how many months did your household reduce or forego expenses for basic household necessities, such as medicine or food, in order to pay an energy bill?
- In the last year, how many months did your household keep your home at a temperature that you felt was unsafe or unhealthy?
- In the last year, how many months did your household receive a disconnection notice, shut off notice, or nondelivery notice for an energy bill?
- Has your household participated in a home energy assistance program that helps pay energy bills or fix broken equipment?
- Has your household received any of the following energy-related benefits or assistance for this home?
    - Free or subsidized energy-efficient light bulbs
    - Free or subsidized home energy audit
    - Utility or energy supplier rebate for new appliance or equipment
    - Recycling of an old appliance or equipment (for example: a refrigerator)
    - Tax credit for new appliance or equipment
    - Other (please specify)

The other RECS variables included in the analysis are geographic. The Census Bureau divides the country into 4 regions and 9 divisions (Figure 1). It also defines an urbanized area as a territory with densely populated tracts totaling at least 50,000 inhabitants; if the total population is between 2,500 and

50,000, it qualifies as an urban cluster.[23] Metropolitan and micropolitan statistical areas are similar, with the former organized around an urbanized area and the latter around an urban cluster.[24]

A.2 Data Preparation

A.2.1 American Community Survey

While the ACS is conducted every year, the Census Bureau also publishes results that are representative of 5 year periods. Because the utility-specific data covers multiple years, we used these 5 year estimates unless otherwise noted. Table A - 1 lists the source census tables and summary files used for the analysis variables. Unless otherwise noted they refer to occupied housing units or the head of household, rather than total population or residential building stock.

Table A-1. ACS tables and sequences

Characteristic	Tract	Block group
Income	S1902	58
Education	S2502	4225
Race and ethnicity	S2502	111
Language – limited English	S1602	44
Tenure	S2502	113
Householder age	S2502	111
Homeownership	S2504	111
Vintage	S2504	113
Building type	S2504	112
Urbanization	HCT1[26]	Delineation File[27]

Most of these variables are reported as the number of households in a particular bin, for example structures built 1939 or earlier, 1940 to 1959, etc. For the analysis we maintained most of this granularity of the data and normalized them to the total number of households in the appropriate geographic area.

A.2.2 Zip Code Aggregation

ACS data is not reported at the zip code level, so we used the tract-to-zip-code crosswalk published by the Department of Housing and Urban Development.[28] Zip codes can be made up of portions of census tracts as well as multiple tracts. If a tract is divided between zip codes, we assume that the

23 https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html
24 https://www.census.gov/programs-surveys/metro-micro.html
25 Educational attainment for the population 25 or older.
26 From the last decennial census, in 2010.
27 Delineation of metropolitan and micropolitan counties. https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/delineation-files.html
28 https://www.huduser.gov/portal/datasets/usps_crosswalk.html

demographics are equally distributed. For example, if Tract A has 100 owner-occupied housing units and 75% of the tract's addresses are in Zip 1 and 25% in Zip 2, we assign 75 owner-occupied units to Zip 1 and 25 to Zip 2. Because medians cannot be allocated in this way, we used mean and binned variables for the zip-code-level data in cases where we used medians for the CBGs.

A.3 Statistical Modeling

A.3.1 Regression Analysis

Logistic regression is used to model binary outcomes. The result of the model is the predicted probability of achieving one of the two outcomes at any combination of the predictor variables. Because the RECS data are at the household level, we have a binary outcome – whether or not the household received the particular kind of assistance. So a logistic model is appropriate for this circumstance.

The regression coefficients for logistic models are difficult to interpret, so we report average marginal effects (AMEs) to convey the magnitude of the relationship between the particular independent variable and the outcome variable. Conceptually, a marginal effect is the slope of the logistic curve with respect to a single variable. The AME is the average of that slope when the other independent variables take on the values of every data point in the dataset. Thus, they indicate the average impact of a unit change in each dependent variable, and can be interpreted in the same manner as the coefficients from a linear regression.

While logistic regression is sometimes used on shares, which vary continuously from 0 to 1, it is not appropriate for our place-based data. The participation rates are clustered very close to zero, which makes the error bands for logistic models very large in regions of the logistic curve where there is very little data. A linear probability model, where the dependent variable is the share of households that participate, is more appropriate in this case.

In both cases we specify our models as a linear combination of all of the explanatory variables. We considered alternate specifications with only a subset of variables, but they did not change the conclusions from the models.

A.3.2 RECS Weighting

The RECS used a multistage area probability sample design to randomly select progressively smaller geographic areas to survey while making sure to get a representative sample.[29] Then they extrapolated from the sample to the whole population with sample weights. The usual standard error calculation is not appropriate with this kind of survey design that employs sample weights because depends on the observations being independent of each other. Consequently we followed the guidance provided with the data and used the survey package[30] in R to take the replicate weights into account when calculating the standard error.

[29] US Energy Information Administration.
https://www.eia.gov/consumption/residential/reports/2015/methodology/index.php
[30] https://cran.r-project.org/web/packages/survey/survey.pdf

A.3.3 Mass Save Details

Rather than aggregating all of the incentives in each zip code over the 6 years of our study period, we use 1 zip code-year as our unit of analysis. This means that each zip code contributes up to 6 data points to the modeling dataset and allows us to include the 69 zip codes that do not have data reported from all 6 years. Because year was a significant variable in our regression models, we do not account for missing data by creating an average incentive value per year in the zip code.

However, there are still two reasons why data from a particular zip code-year may not be included in the analysis. First, we dropped zip-code years with incentives that were clear outliers based on gaps in incentives. On the electric side our cutoff was $700 per household per year, and for gas it was $400 per household per year. Second, 28 zip codes have Mass Save data but are not allocated any residential addresses from HUD's tract-to-zip-code crosswalk.

Appendix B. Correlation Coefficients

Many of the household and physical characteristics we consider are related to each other. Tables B - 1 through B - 4 show the correlation coefficients between these factors for the RECS, Mass Save, National Grid Rhode Island, and Utility A.

Table B-1. RECS correlation matrix

	Income[31]	Bachelor's degree or higher	Non-Latino White	Black	Latino White	Reduce or forego basic necessities due to energy bill at least 1 month	Keep home at unhealthy temperature at least 1 month	Receive disconnect notice at least 1 month	Householder age	Single-family home	Urban area or cluster
Income	1	0.45	0.08	-0.11	-0.05	-0.26	-0.16	-0.17	-0.23	0.18	0.08
Bachelor's degree or higher	0.45	1	0.05	-0.05	-0.08	-0.17	-0.09	-0.14	-0.12	0.09	0.13
Non-Latino White	0.08	0.05	1			-0.16	-0.10	-0.15	0.14	0.06	-0.12
Black	-0.11	-0.05		1		0.13	0.06	0.15	0.00	-0.01	0.00
Latino White	-0.05	-0.08			1	0.08	0.09	0.07	-0.12	-0.03	0.12
Reduce or forego basic necessities due to energy bill at least 1 month	-0.26	-0.17	-0.16	0.13	0.08	1	0.41	0.40	-0.10	-0.11	-0.03
Keep home at unhealthy temperature at least 1 month	-0.16	-0.09	-0.10	0.06	0.09	0.41	1	0.21	-0.01	-0.08	0.00
Receive disconnect notice at least 1 month	-0.17	-0.14	-0.15	0.15	0.07	0.40	0.21	1	-0.14	-0.08	-0.04
Householder age	-0.23	-0.12	0.14	0.00	-0.12	-0.10	-0.01	-0.14	1	0.01	-0.03
Single-family home	0.18	0.09	0.06	-0.01	-0.03	-0.11	-0.08	-0.08	0.01	1	0.06
Urban area or cluster	0.08	0.13	-0.12	0.00	0.12	-0.03	0.00	-0.04	-0.03	0.06	1

[31] In the RECS income is divided into 8 bins, 7 of which are of equal width ($20k). The remaining bin is unbounded: “$140k and up”.

Table B-2. Mass Save correlation matrix

	Mean income	Bachelor's degree or higher	Non-Latino White	Black	Latino White	Limited English	Mean energy burden	Mean householder age[32]	Owner-occupied	Single-family home	Urban zip code
Mean income	1	0.83	0.28	-0.28	-0.34	-0.32	-0.64	0.19	0.41	0.32	0.05
Bachelor's degree or higher	0.83	1	0.24	-0.29	-0.33	-0.30	-0.63	0.10	0.23	0.14	0.09
Non-Latino White	0.28	0.24	1			-0.86	-0.07	0.57	0.76	0.73	-0.40
Black	-0.28	-0.29		1		0.49	0.19	-0.34	-0.48	-0.45	0.26
Latino White	-0.34	-0.33			1	0.73	0.21	-0.41	-0.60	-0.53	0.26
Limited English	-0.32	-0.30	-0.86	0.49	0.73	1	0.05	-0.48	-0.75	-0.73	0.32
Mean energy burden	-0.64	-0.63	-0.07	0.19	0.21	0.05	1	0.20	-0.02	0.12	-0.30
Mean householder age	0.19	0.10	0.57	-0.34	-0.41	-0.48	0.20	1	0.68	0.67	-0.25
Owner-occupied	0.41	0.23	0.76	-0.48	-0.60	-0.75	-0.02	0.68	1	0.94	-0.43
Single-family home	0.32	0.14	0.73	-0.45	-0.53	-0.73	0.12	0.67	0.94	1	-0.45
Urban zip code	0.05	0.09	-0.40	0.26	0.26	0.32	-0.30	-0.25	-0.43	-0.45	1

[32] The ACS reports householder age in bins of 10 years, starting at 35 and ending at 85; the bins on either side are unbounded (i.e. under 35 years and 80 years and above). To calculate the mean age for the geographic area (zip code or CBG), we take the midpoint of each bounded bin and 30 and 90 for the unbounded ones.

Table B-3. National Grid Rhode Island correlation matrix

	Mean income	Bachelor's degree or higher	Non-Latino White	Black	Latino White	Limited English	Mean energy burden	Mean householder age	Owner-occupied	Single-family home	Urban zip code
Mean income	1	0.80	0.71	-0.71	-0.71	-0.69	-0.67	0.51	0.73	0.74	-0.32
Bachelor's degree or higher	0.80	1	0.47	-0.52	-0.52	-0.47	-0.79	0.39	0.37	0.44	-0.09
Non-Latino White	0.71	0.47	1			-0.91	-0.45	0.67	0.84	0.84	-0.41
Black	-0.71	-0.52		1		0.76	0.53	-0.65	-0.74	-0.74	0.38
Latino White	-0.71	-0.52			1	0.88	0.56	-0.60	-0.78	-0.78	0.39
Limited English	-0.69	-0.47	-0.91	0.76	0.88	1	0.40	-0.49	-0.82	-0.82	0.36
Mean energy burden	-0.67	-0.79	-0.45	0.53	0.56	0.40	1	-0.19	-0.29	-0.31	0.10
Mean householder age	0.51	0.39	0.67	-0.65	-0.60	-0.49	-0.19	1	0.62	0.68	-0.25
Owner-occupied	0.73	0.37	0.84	-0.74	-0.78	-0.82	-0.29	0.62	1	0.97	-0.62
Single-family home	0.74	0.44	0.84	-0.74	-0.78	-0.82	-0.31	0.68	0.97	1	-0.62
Urban zip code	-0.32	-0.09	-0.41	0.38	0.39	0.36	0.10	-0.25	-0.62	-0.62	1

Table B-4. Utility A correlation matrix

	Median income	Bachelor's degree or higher	Non-Latino White	Black	Latino White	Limited English	Mean energy burden	Mean householder age	Owner-occupied	Single-family home	Metropolitan CBG
Median income	1	0.58	0.45	-0.42	-0.18	-0.19	-0.45	0.22	0.66	0.46	0.02
Bachelor's degree or higher	0.58	1	0.28	-0.22	-0.19	-0.18	-0.52	0.13	0.30	0.13	0.18
Non-Latino White	0.45	0.28	1			-0.36	-0.31	0.22	0.52	0.24	-0.33
Black	-0.42	-0.22		1		0.11	0.29	-0.10	-0.46	-0.19	0.29
Latino White	-0.18	-0.19			1	0.48	0.08	-0.24	-0.20	-0.09	0.16
Limited English	-0.19	-0.18	-0.36	0.11	0.48	1	0.07	-0.19	-0.23	-0.14	0.04
Mean energy burden	-0.45	-0.52	-0.31	0.29	0.08	0.07	1	0.01	-0.23	-0.07	-0.29
Mean householder age	0.22	0.13	0.22	-0.10	-0.24	-0.19	0.01	1	0.44	0.25	-0.11
Owner-occupied	0.66	0.30	0.52	-0.46	-0.20	-0.23	-0.23	0.44	1	0.73	-0.12
Single-family home	0.46	0.13	0.24	-0.19	-0.09	-0.14	-0.07	0.25	0.73	1	-0.02
Metropolitan CBG	0.02	0.18	-0.33	0.29	0.16	0.04	-0.29	-0.11	-0.12	-0.02	1

Appendix C. Multivariable Regression Results

Tables C - 1 through C - 3 contain the results of the multivariable regression models for the RECS, Mass Save, and Utility A. Single-variable regression results are available on request.

C.1 RECS

Table C-1. RECS regression results – logistic model

	Dependent variable:									
	Efficient Lights (1)		Free or Subsidized Audit (2)		Appliance Rebate (3)		Appliance Recycling (4)		Any Assistance (5)	
	Coefficient & SE	AME	Coefficient & SE	AME	Coefficient & SE	AME	Coefficient & SE	AME	Coefficient & SE	AME
Census division (compared to "New England")										
Middle Atlantic	-0.411	-0.044	-1.393	-0.058	-0.268	-0.018	0.776**	0.061	-0.149	-0.029
	(-0.349)		(-0.781)		(-0.352)		(-0.253)		(-0.266)	
East North Central	-0.372	-0.04	-1.253	-0.055	-0.860*	-0.046	0.590*	0.043	-0.219	-0.043
	(-0.325)		(-0.767)		(-0.33)		(-0.237)		(-0.228)	
West North Central	-2.475***	-0.137	-1.597	-0.063	-0.223	-0.015	0.679*	0.052	-0.655*	-0.116
	(-0.552)		(-0.897)		(-0.362)		(-0.26)		(-0.283)	
South Atlantic	-1.122**	-0.094	-1.495	-0.061	-0.744*	-0.042	0.014	0.001	-0.840**	-0.143
	(-0.349)		(-0.757)		(-0.345)		(-0.236)		(-0.246)	
East South Central	-1.465*	-0.11	-2.548	-0.077	-0.835*	-0.045	-0.869	-0.035	-1.265***	-0.193
	(-0.648)		(-1.283)		(-0.346)		(-0.52)		(-0.328)	
West South Central	-1.839***	-0.123	-0.96	-0.046	-0.690*	-0.039	-0.461	-0.022	-1.231***	-0.189
	(-0.426)		(-0.809)		(-0.32)		(-0.365)		(-0.233)	

	Efficient Lights		Free or Subsidized Audit		Appliance Rebate		Appliance Recycling		Any Assistance	
Mountain North	-0.643	-0.063	-1.364	-0.058	-0.107	-0.008	0.722	0.056	-0.153	-0.03
	(-0.349)		(-0.833)		(-0.404)		(-0.418)		(-0.298)	
Mountain South	-1.727**	-0.119	-0.575	-0.031	-0.18	-0.013	0.978**	0.084	-0.215	-0.042
	(-0.6)		(-0.938)		(-0.474)		(-0.305)		(-0.281)	
Pacific	-0.523	-0.053	-1.427	-0.059	0.095	0.007	0.639*	0.048	-0.037	-0.007
	(-0.29)		(-0.811)		(-0.322)		(-0.249)		(-0.223)	
Educational attainment (compared to "Less than high school diploma")										
High school diploma or GED	0.234	0.014	2.027	0.024	0.007	0	0.151	0.008	0.058	0.008
	(-0.33)		(-1.226)		(-0.579)		(-0.414)		(-0.217)	
Some college or Associate's degree	0.242	0.015	2.194	0.028	0.4	0.018	0.563	0.037	0.352	0.052
	(-0.365)		(-1.214)		(-0.57)		(-0.376)		(-0.218)	
Bachelor's degree	0.078	0.004	2.337	0.032	0.761	0.039	0.672	0.046	0.51	0.079
	(-0.37)		(-1.259)		(-0.576)		(-0.403)		(-0.253)	
Graduate degree	0.391	0.025	2.870*	0.051	0.539	0.025	0.768	0.054	0.629*	0.1
	(-0.376)		(-1.26)		(-0.603)		(-0.404)		(-0.245)	
Income (compared to "Less than $20k")										
$20- 40k	-0.229	-0.021	-0.867	-0.026	0.25	0.012	-0.018	-0.001	-0.147	-0.025
	(-0.316)		(-0.456)		(-0.49)		(-0.34)		(-0.223)	

	Efficient Lights		Free or Subsidized Audit		Appliance Rebate		Appliance Recycling		Any Assistance	
$40 - 60k	-0.506	-0.041	-0.448	-0.016	0.142	0.006	0.311	0.023	-0.202	-0.034
	(-0.275)		(-0.461)		(-0.449)		(-0.323)		(-0.192)	
$60 - 80k	-0.662	-0.051	-0.633	-0.021	0.305	0.014	0.444	0.034	-0.201	-0.034
	(-0.332)		(-0.44)		(-0.457)		(-0.343)		(-0.183)	
$80 - 100k	-0.693*	-0.053	-0.407	-0.014	0.641	0.035	0.04	0.003	-0.239	-0.04
	(-0.33)		(-0.448)		(-0.459)		(-0.364)		(-0.236)	
$100 - 120k	-0.758	-0.057	-0.561	-0.019	0.081	0.003	0.444	0.034	-0.23	-0.038
	(-0.378)		(-0.545)		(-0.516)		(-0.361)		(-0.249)	
$120 - 140k	-0.63	-0.049	-0.732	-0.023	0.438	0.022	0.112	0.007	-0.244	-0.041
	(-0.394)		(-0.546)		(-0.513)		(-0.382)		(-0.259)	
$140k or more	-1.228***	-0.079	-0.817	-0.025	0.387	0.019	0.5	0.039	-0.195	-0.033
	(-0.334)		(-0.55)		(-0.498)		(-0.352)		(-0.243)	
Frequency of reducing or forgoing basic necessities due to home energy bill (compared to "Never")										
1-2 months	-0.559	-0.03	0.885*	0.031	0.489	0.031	-0.659	-0.042	-0.172	-0.027
	(-0.398)		(-0.435)		(-0.396)		(-0.352)		(-0.278)	
Some months	0.048	0.003	0.448	0.013	0.298	0.017	-0.434	-0.03	0.061	0.01
	(-0.221)		(-0.385)		(-0.375)		(-0.303)		(-0.178)	
Almost every month	-0.127	-0.008	0.882	0.031	0.274	0.016	-0.314	-0.023	0.015	0.002
	(-0.432)		(-0.53)		(-0.468)		(-0.456)		(-0.288)	

	Efficient Lights		Free or Subsidized Audit		Appliance Rebate		Appliance Recycling		Any Assistance	
Frequency of keeping home at unhealthy temperature (compared to "Never")										
1-2 months	0.608	0.05	0.256	0.008	-0.436	-0.019	0.825	0.084	0.822	0.156
	(-0.527)		(-0.777)		(-0.796)		(-0.531)		(-0.424)	
Some months	-0.188	-0.012	0.303	0.009	-0.382	-0.017	0.244	0.02	0.071	0.012
	(-0.446)		(-0.51)		(-0.604)		(-0.353)		(-0.262)	
Almost every month	-0.493	-0.027	0.018	0	0.303	0.018	-0.084	-0.006	-0.281	-0.042
	(-0.384)		(-0.695)		(-0.484)		(-0.316)		(-0.22)	
Frequency of receiving disconnect notice (compared to "Never")										
1-2 months	0.101	0.007	-0.261	-0.007	0.041	0.002	0.06	0.005	-0.009	-0.001
	(-0.414)		(-0.657)		(-0.343)		(-0.324)		(-0.227)	
Some months	0.225	0.016	0.08	0.002	0.209	0.012	-0.029	-0.002	0.059	0.01
	(-0.399)		(-0.51)		(-0.432)		(-0.47)		(-0.289)	
Almost every month	0.704	0.059	-17.065*	-0.036	-1.287	-0.041	-0.546	-0.035	-0.209	-0.032
	(-0.601)		(-7.861)		(-1.165)		(-1.116)		(-0.471)	
Frequency of draft (compared to "Never")										
Some of the time	0.034	0.002	0.411	0.011	-0.277	-0.015	-0.063	-0.005	-0.08	-0.013
	(-0.149)		(-0.275)		(-0.15)		(-0.12)		(-0.089)	

	Efficient Lights		Free or Subsidized Audit		Appliance Rebate		Appliance Recycling		Any Assistance	
Most of the time	0.062	0.004	0.293	0.008	-0.611	-0.029	0.301	0.026	0.014	0.002
	(-0.329)		(-0.516)		(-0.426)		(-0.267)		(-0.176)	
All the time	0.483	0.037	0.248	0.006	-0.319	-0.017	-0.448	-0.03	0.081	0.014
	(-0.36)		(-0.722)		(-0.545)		(-0.709)		(-0.266)	
Race and ethnicity (compared to “Non-Latino White”)										
Black or African/American Alone	0.391	0.029	-0.086	-0.002	-0.356	-0.018	-0.43	-0.03	0.137	0.023
	(-0.261)		(-0.568)		(-0.418)		(-0.327)		(-0.214)	
American Indian or Alaska Native Alone	-1.675*	-0.058	-16.099*	-0.037	-1.155	-0.042	-1.098	-0.061	-1.302*	-0.152
	(-0.772)		(-7.84)		(-0.858)		(-0.765)		(-0.558)	
Asian Alone	-0.291	-0.017	-0.022	-0.001	-0.276	-0.014	-0.619	-0.041	-0.575*	-0.082
	(-0.324)		(-0.592)		(-0.384)		(-0.413)		(-0.229)	
Native Hawaiian or Other Pacific Islander Alone	0.648	0.052	-16.469*	-0.037	-12.151	-0.064	-11.994	-0.097	-0.895	-0.118
	(-1.157)		(-7.97)		(-7.957)		(-7.959)		(-0.995)	
2 or More Races	-0.107	-0.006	0.488	0.017	-0.676	-0.03	0.246	0.022	0.085	0.014
	(-0.647)		(-0.901)		(-0.774)		(-0.479)		(-0.306)	
White Alone and Hispanic or Latino	0.401	0.03	-0.764	-0.017	-0.684*	-0.03	-0.396	-0.028	-0.295	-0.046
	(-0.203)		(-0.46)		(-0.317)		(-0.286)		(-0.164)	

	Efficient Lights		Free or Subsidized Audit		Appliance Rebate		Appliance Recycling		Any Assistance	
Householder age										
Householder age	0.004	0	0.005	0	-0.003	0	0.005	0	0.005	0.001
	(-0.006)		(-0.008)		(-0.007)		(-0.005)		(-0.004)	
Tenure (compared to "Moved in before 1980")										
Moved in 1980-1989	0.528	0.035	0.045	0.001	0.189	0.011	-0.155	-0.014	0.093	0.016
	(-0.292)		(-0.45)		(-0.382)		(-0.24)		(-0.172)	
Moved in 1990-1999	0.111	0.006	-0.033	-0.001	0.234	0.014	0.14	0.014	0.146	0.026
	(-0.288)		(-0.345)		(-0.334)		(-0.187)		(-0.158)	
Moved in 2000-2009	0.457	0.03	0.112	0.003	-0.08	-0.004	-0.444	-0.037	-0.103	-0.017
	(-0.311)		(-0.369)		(-0.338)		(-0.221)		(-0.195)	
Moved in 2010-2015	0.058	0.003	-0.262	-0.007	-0.259	-0.013	-0.830**	-0.06	-0.428	-0.066
	(-0.344)		(-0.414)		(-0.412)		(-0.25)		(-0.239)	
Vintage (compared to "Built before 1950")										
Built 1950-1959	-0.398	-0.029	0.084	0.002	0.483	0.025	0.256	0.02	0.03	0.005
	(-0.308)		(-0.413)		(-0.359)		(-0.204)		(-0.178)	
Built 1960-1969	-0.662*	-0.045	0.238	0.007	0.399	0.02	0.630*	0.056	0.135	0.023
	(-0.291)		(-0.452)		(-0.311)		(-0.252)		(-0.163)	

	Efficient Lights		Free or Subsidized Audit		Appliance Rebate		Appliance Recycling		Any Assistance	
Built 1970-1979	-0.288	-0.022	-0.318	-0.008	0.393	0.019	0.111	0.008	-0.073	-0.012
	(-0.249)		(-0.449)		(-0.331)		(-0.222)		(-0.147)	
Built 1980-1989	-0.601	-0.041	0.154	0.005	0.307	0.014	0.076	0.005	-0.155	-0.025
	(-0.307)		(-0.469)		(-0.296)		(-0.235)		(-0.185)	
Built 1990-1999	-0.222	-0.017	0.229	0.007	0.157	0.007	0.016	0.001	-0.106	-0.017
	(-0.318)		(-0.368)		(-0.318)		(-0.226)		(-0.178)	
Built 2000-2009	-0.55	-0.039	-0.619	-0.014	0.393	0.019	0.2	0.015	-0.143	-0.023
	(-0.31)		(-0.494)		(-0.264)		(-0.276)		(-0.171)	
Built 2010-2015	-0.599	-0.041	-15.817	-0.036	0.473	0.024	-1.594***	-0.062	-0.698*	-0.098
	(-0.565)		(-7.821)		(-0.42)		(-0.431)		(-0.321)	
Building type (compared to "Single-family detached house")										
Single-family attached house	-0.237	-0.015	-0.261	-0.007	-0.651	-0.028	0.391	0.035	-0.011	-0.002
	(-0.256)		(-0.362)		(-0.398)		(-0.204)		(-0.161)	
Apartment in a building with 2-4 units	-0.345	-0.021	-0.751	-0.017	0.411	0.027	0.428	0.039	-0.145	-0.024
	(-0.696)		(-1.097)		(-0.562)		(-0.497)		(-0.402)	
Apartment in a building with 5 or more units	-0.611	-0.033	-16.651*	-0.037	-1.409***	-0.045	-0.832	-0.048	-1.032***	-0.131
	(-0.482)		(-7.707)		(-0.228)		(-0.431)		(-0.279)	

	Efficient Lights		Free or Subsidized Audit		Appliance Rebate		Appliance Recycling		Any Assistance	
Mobile home	-0.344	-0.021	-1.034	-0.021	-0.409	-0.019	-0.366	-0.025	-0.621*	-0.089
	(-0.343)		(-0.578)		(-0.443)		(-0.42)		(-0.247)	
Urbanization (compared to "Rural")										
Urban cluster	0.092	0.006	0.514	0.017	-0.879*	-0.038	-0.16	-0.012	-0.264	-0.041
	(-0.223)		(-0.367)		(-0.332)		(-0.245)		(-0.19)	
Urban area	-0.006	0	-0.086	-0.002	-0.181	-0.01	0.036	0.003	-0.061	-0.01
	(-0.21)		(-0.304)		(-0.171)		(-0.187)		(-0.128)	
Internet (compared to "No internet at home")										
Internet at home	0.066	0.004	0.812	0.018	0.314	0.015	0.198	0.014	0.366*	0.055
	(-0.235)		(-0.577)		(-0.424)		(-0.254)		(-0.173)	
Assistance types (compared to not receiving the assistance)										
Bill or appliance repair assistance	0.563	0.045	1.111	0.043	0.763*	0.054	1.084***	0.118	1.002***	0.194
	(-0.282)		(-0.557)		(-0.347)		(-0.287)		(-0.2)	
Free or subsidized audit	-0.291***	-0.019			-0.047	-0.003	0.074*	0.006		
	(-0.064)				(-0.076)		(-0.034)			
Efficient lights			2.750***	0.075	0.583*	0.031	-0.197*	-0.015		
			(-0.274)		(-0.251)		(-0.086)			

	Efficient Lights		Free or Subsidized Audit		Appliance Rebate		Appliance Recycling		Any Assistance	
Appliance rebate	0.672**	0.044	-0.468	-0.013	0		0.131	0.01		
	(-0.212)		(-0.295)		()		(-0.22)			
Appliance recycling	-0.066	-0.004	-0.074	-0.002	0.156	0.008				
	(-0.139)		(-0.132)		(-0.183)					
Constant										
Constant	-1.695*		-5.630**		-3.174**		-3.748***		-1.290*	
	(-0.714)		(-1.71)		(-0.98)		(-0.643)		(-0.49)	
Observations	3,774		3,748		3,770		3,766		3,771	
Log Likelihood	-988.412		-449.451		-853.211		-1,105.64		-2,011.07	
Akaike Inf. Crit.	2,100.83		1,022.90		1,830.42		2,335.28		4,140.14	

Notes: AME is “average marginal effect”. See Section A.3.1 for more details. *p<0.05; **p<0.01; ***p<0.001

C.2 Mass Save

Table C-2. Mass Save regression results – linear model

	Dependent variable:
	Electric Incentives
Educational attainment (compared to "Less than high school graduate")	
High school graduate	79.133*
	(30.873)
Some college or associate's degree	22.347
	(29.706)
Bachelor's degree or higher	166.120***
	(25.560)
Income	
Mean income	0.00004
	(0.00004)
Energy burden	
Mean energy burden	2,029.328***
	(115.555)
Race and ethnicity (compared to "Non-Latino White")	
Black	0.657
	(10.064)
White, Hispanic or Latino	-115.474***
	(18.375)
Asian	-131.388***
	(18.208)
Other	-87.335***
	(23.416)
Limited English (compared to "Not limited English")	
Limited English	412.048***
	(35.721)

Householder age (compared to "Less than 35 years")	
35 to 44 years	-75.182* (29.878)
45 to 54 years	-59.544* (25.281)
55 to 64 years	155.720*** (24.902)
65 to 74 years	-55.365* (26.706)
75 to 84 years	315.877*** (37.368)
85 years and over	-112.606** (38.316)
Tenure (compared to "Moved in before 1990")	
Moved in 2015 or later	118.768*** (32.228)
Moved in 2010 to 2014	35.685 (25.129)
Moved in 2000 to 2009	140.133*** (24.440)
Moved in 1990 to 1999	-12.779 (30.698)
Building type (compared to "Single-family home")	
2-4 units	-94.953*** (15.954)
5-9 units	-136.826*** (24.671)
10+ units	-59.956*** (14.954)
Other	-147.863*** (30.291)

Vintage (compared to “Built before 1940”)	
Built 2010 or later	83.093* (36.352)
Built 2000-2009	25.244 (20.265)
Built 1980-1999	26.389* (11.017)
Built 1960-1979	5.708 (10.083)
Built 1940-1959	-88.173*** (13.884)
Occupancy (compared to “Renter occupied”)	
Owner occupied	-0.484 (18.114)
Urbanization (compared to “Rural”)	
Urban	14.637*** (3.094)
Incentive year (compared to “2013”)	
2014	14.186*** (2.127)
2015	28.402*** (2.128)
2016	31.076*** (2.127)
2017	41.863*** (2.124)
2018	51.811*** (2.127)
Constant	
Constant	-179.211*** (38.160)
Observations	9,392
R^2	0.299

Adjusted R^2	0.297
Residual Std. Error	58.066 (df = 9355)
F Statistic	111.052*** (df = 36; 9355)
Note:	*p<0.05; **p<0.01; ***p<0.001

C.3 Utility A

Table C-3. Utility A regression results – linear model

	Any Program	Any Market-Rate Program	IQ Audit & DI	Audit & DI	HVAC Rebate	Appliance Recycling
	(1)	(2)	(3)	(4)	(5)	(6)
Educational attainment (compared to "Less than high school graduate")						
High school graduate	0.003	-0.003	0.005*	0.001	-0.006	0.002
	(0.008)	(0.007)	(0.002)	(0.001)	(0.006)	(0.003)
Some college or associate's degree	0.017*	0.015*	0.002	0.001	0.008	0.004
	(0.008)	(0.007)	(0.002)	(0.001)	(0.006)	(0.003)
Bachelor's degree or higher	0.066***	0.061***	0.005*	0.008***	0.047***	0.009***
	(0.007)	(0.007)	(0.002)	(0.001)	(0.005)	(0.003)
Income						
Median income	1.007e-07*	1.258e-07**	-2.465e-08*	-1.151e-08	1.264e-07***	8.876e-09
	(4.230e-08)	(4.061e-08)	(1.140e-08)	(6.808e-09)	(3.181e-08)	(1.494e-08)
Energy burden						
Mean energy burden	-0.416***	-0.407***	-0.01	-0.034***	-0.277***	-0.099***
	(0.058)	(0.056)	(0.016)	(0.009)	(0.044)	(0.021)
Race and ethnicity (compared to "Non-Latino White")						
Black	0.017***	-0.006*	0.024***	0.007***	-0.01***	-0.003**
	(0.003)	(0.003)	(8.502e-04)	(5.076e-04)	(0.002)	(0.001)
White, Hispanic or Latino	0.027**	0.026**	7.895e-04	4.676e-04	0.017*	0.011**
	(0.01)	(0.009)	(0.003)	(0.002)	(0.007)	(0.003)
Asian	0.018	0.018	-6.975e-04	-0.003	0.016	0.002
	(0.019)	(0.018)	(0.005)	(0.003)	(0.014)	(0.007)
Other	0.001	-0.01	0.011***	3.811e-04	-0.01	-0.003
	(0.008)	(0.008)	(0.002)	(0.001)	(0.006)	(0.003)

	Any Program	Any Market-Rate Program	IQ Audit & DI	Audit & DI	HVAC Rebate	Appliance Recycling
Limited English (compared to "Not limited English")						
Limited English	-0.011	0.002	-0.012*	0.004	-0.005	0.006
	(0.018)	(0.017)	(0.005)	(0.003)	(0.013)	(0.006)
Householder age (compared to "Less than 35 years")						
35 to 44 years	-0.002	4.207e-04	-0.002	-0.001	-4.264e-04	8.548e-04
	(0.008)	(0.008)	(0.002)	(0.001)	(0.006)	(0.003)
45 to 54 years	0.006	0.006	1.135e-04	5.618e-04	0.004	0.001
	(0.008)	(0.008)	(0.002)	(0.001)	(0.006)	(0.003)
55 to 64 years	0.023**	0.021*	0.003	0.002	0.019**	1.513e-04
	(0.008)	(0.008)	(0.002)	(0.001)	(0.006)	(0.003)
65 to 74 years	0.035***	0.029***	0.007**	0.004*	0.025***	-1.855e-04
	(0.009)	(0.009)	(0.002)	(0.001)	(0.007)	(0.003)
75 to 84 years	0.044***	0.044***	0.001	0.008***	0.034***	0.004
	(0.011)	(0.011)	(0.003)	(0.002)	(0.008)	(0.004)
85 years and over	0.064***	0.054***	0.009*	0.006**	0.042***	0.009
	(0.014)	(0.014)	(0.004)	(0.002)	(0.011)	(0.005)
Tenure						
Median year moved in	4.680e-04**	5.265e-04**	-5.103e-05	6.523e-06	5.589e-04***	-1.032e-04
	(1.671e-04)	(1.604e-04)	(4.506e-05)	(2.690e-05)	(1.257e-04)	(5.902e-05)
Vintage						
Median year structure built	7.497e-05	9.788e-05*	-2.830e-05*	2.571e-06	1.154e-04***	-3.061e-05
	(4.479e-05)	(4.300e-05)	(1.208e-05)	(7.210e-06)	(3.369e-05)	(1.582e-05)
Building type (compared to "Single-family home")						
2-4 units	5.948e-04	0.004	-0.003	-0.001	0.001	0.003
	(0.009)	(0.008)	(0.002)	(0.001)	(0.007)	(0.003)
5-9 units	-0.028**	-0.02*	-0.008**	-0.002	-0.014	-0.002
	(0.01)	(0.009)	(0.003)	(0.002)	(0.007)	(0.003)
10+ units	-0.041***	-0.03***	-0.011***	-0.006***	-0.023***	-0.002
	(0.007)	(0.006)	(0.002)	(0.001)	(0.005)	(0.002)
Other	-0.025***	-0.025***	8.403e-04	-4.958e-04	-0.02***	-0.004
	(0.006)	(0.006)	(0.002)	(0.001)	(0.005)	(0.002)
Occupancy (compared to "Renter occupied")						
Owner occupied	0.011	0.012*	-8.490e-04	-2.767e-04	0.009	0.002
	(0.006)	(0.006)	(0.002)	(9.817e-04)	(0.005)	(0.002)

	Any Program	Any Market-Rate Program	IQ Audit & DI	Audit & DI	HVAC Rebate	Appliance Recycling
Urbanization (compared to "Metropolitan area")						
Micropolitan area	-0.012***	-0.012***	-4.958e-04	-8.451e-04***	-0.008***	-0.003***
	(0.002)	(0.001)	(4.150e-04)	(2.478e-04)	(0.001)	(5.437e-04)
Rural	-0.017***	-0.016***	-0.001	-0.001**	-0.01***	-0.005***
	(0.002)	(0.002)	(5.899e-04)	(3.522e-04)	(0.002)	(7.728e-04)
Electric territory (compared to "Electric service not from Utility A")						
Electric service from Utility A	0.023***	0.02***	0.004***	0.004***	0.004***	0.013***
	(0.001)	(0.001)	(2.998e-04)	(1.790e-04)	(8.362e-04)	(3.927e-04)
Constant						
Constant	-1.096***	-1.256***	0.155	-0.02	-1.35***	0.264*
	(0.332)	(0.319)	(0.09)	(0.053)	(0.25)	(0.117)
Observations	1496	1496	1496	1496	1496	1496
Log Likelihood	3.767e+03	3.828e+03	5.728e+03	6.499e+03	4.193e+03	5.324e+03
Akaike Inf. Crit.	-7.480e+03	-7.602e+03	-1.140e+04	-1.294e+04	-8.332e+03	-1.059e+04
Note:						*p<0.05; **p<0.01; ***p<0.001